The Digital Divide in U.S. Mobile Technology and Speeds

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Abstract

High-speed Internet access, or broadband, is critical to economic opportunity, job creation, education, and civic engagement. Yet, there is a digital divide between people who have access to high speed Internet/advanced telecommunications, and those who do not. Currently, most of the discussion regarding the digital divide focuses on access to fixed broadband networks. In this paper, we examine the digital divide as it relates to mobile broadband. Specifically, we explore the following two research questions. First, is there a digital divide in how certain groups access mobile broadband as measured by the mobile connection technology? Second, is there a digital divide in the quality of their mobile broadband as measured by download and upload speeds? We investigate the first question by running a multinomial logit of the type of on-air connection (WiFi vs. 3G, Non-LTE 4G, or LTE) on U.S. county demographics and characteristics, as well as technological variables; and we investigate the second question by running separate OLS regressions of log download and upload speed for each technology on U.S. county demographics and characteristics, and technological variables. Connection technology and speed data from the last six months of 2016 are obtained from the Ookla Speedtest app, and U.S. Census data are used to provide local demographic information and other county characteristics. Overall, we conclude that the mobile digital divide does exist across certain dimensions. Rural areas are somewhat more dependent on non-WiFi mobile technology and experience slower speeds on their mobile connections. We also find that counties with higher minority populations are more likely to use older mobile technologies and experience slower speeds. Counties with older populations are more likely to use mobile technologies and are more likely to have slower speeds. Counties with larger households are more likely to use WiFi and also have faster WiFi. Indicators of economic health, as well as technological and infrastructure related variables, have mixed and complicated effects. These complex results suggest that future research and on-the-ground data are necessary to further examine the nature of the mobile digital divide.

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Judith Dempsey and Patrick Sun[1]

1. Introduction

Americans today depend on the Internet for many facets of daily life, including access to employment, education, entertainment, and health care opportunities. Thus, consumers expect and require high-speed broadband at home, at work, and while on the go. But there are still too many parts of this country where broadband is unavailable, and too many populations that are underserved. The Federal Communications Commission (FCC) has recognized the importance of providing high-speed Internet access to all Americans, and one of the Commission's top priorities is to close the digital divide between those who have access to cutting-edge communications services and those who do not.[2] In addition, Congress has tasked the Commission with "encourag[ing] the deployment on a reasonable and timely basis of advanced telecommunications capability to all Americans,"[3] and to regularly report on the progress of this deployment.[4]

A 1999 National Telecommunications and Information Administration (NTIA) report gave an iconic definition of the digital divide as: "the divide between those with access to new technologies and those without."[5] We focus on a different but related divide – the digital divide in the quality of service experienced by different demographic groups. In our framework, improved quality includes newer technology or higher speeds. While most of the discussion regarding the digital divide focuses on access to fixed broadband networks, we focus specifically on mobile broadband. Mobile broadband is an increasingly important part of

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[2] FCC, *Bridging the Digital Divide for All Americans*, https://www.fcc.gov/about-fcc/fcc-initiatives/bridging-digital-divide-all-americans (last visited Dec. 9, 2020).

[3] 47 U.S.C. § 1302(a). Congress also trusted this responsibility to state commissions.

[4] 47 U.S.C. § 1302(b). This requirement was updated on March 23, 2018, when the President signed into law the Consolidated Appropriations Act of 2018, which included the Repack Airwaves Yielding Better Access for Users of Modern Services Act of 2018 (RAY BAUM'S Act of 2018). Title IV of RAY BAUM'S Act of 2018 amends section 13 of the Communications Act of 1934, and requires the Commission, "in the last quarter of every even numbered year" to publish a "Communications Marketplace Report," that, among other things, "assess[es] the state of deployment of communications capabilities, including advanced telecommunications capability (as defined in section 706 of the Telecommunications Act of 1996 (47 U.S.C. [section]1302)), regardless of the technology used for such deployment." *See* Section 13 of the Communications Act of 1934, as amended (Section 13 of the Act) and RAY BAUM'S Act of 2018 § 401, 132 Stat. at 1087-88.

[5] NTIA, *Falling Through the Net: Defining the Digital Divide* (July 08, 1999), https://www.ntia.doc.gov/legacy/ntiahome/fttn99/contents.html. (NTIA 1999).

telecommunications networks in this country. It tends to be cheaper and more flexible than fixed broadband and may be available in areas that are not currently reached by fixed broadband networks.

FCC data from year-end 2017 suggest that not all consumers have access to high quality mobile service.[6] If high-speed mobile broadband is defined as LTE with minimum advertised download/upload speeds of 5/1 Mbps, then 0.2% of Americans do not have access to high-speed mobile service, with that number rising to 0.9% in rural areas and to approximately 3% on Tribal lands.[7] If it is further specified that in addition to LTE coverage, high-speed mobile service requires median actual speeds of 10/3 Mbps, then approximately 11% of all Americans and approximately 31% of Americans in rural areas do not have access.[8]

In order to better address this digital divide in mobile services, we must first understand the factors that cause a community to be more or less likely to have access to these services. Specifically, we explore the following two research questions. First, is there a digital divide in how certain groups access mobile broadband as measured by the mobile connection technology? Second, is there a digital divide in the quality of their mobile broadband as measured by download and upload speed?

To investigate the digital divide in technology types, we run a multinomial logit of the type of on-air connection (WiFi vs. 3G, Non-LTE 4G, or LTE) [9] on U.S. county demographics and characteristics, as well as technological variables. To investigate the digital divide in quality, we run separate ordinary least squares (OLS) regressions of log download and upload speed for each technology on U.S. county demographics and characteristics, and technological variables.[10] Connection technology and speed data are obtained from the Ookla Speedtest app from the last six months of 2016. This is combined with U.S. Census data from the same time period, which are used to provide local demographic information and other county characteristics.

As seen in Table 1, we find evidence consistent with a digital divide of differential access to newer over older technologies. For convenience, we will use the term “mobile” to refer to three progressively newer and higher quality technologies: 3G, Non-LTE 4G, and LTE. We will not refer to WiFi as “mobile” broadband, although we acknowledge that WiFi can be used outside of the home on mobile handsets. We consider WiFi a separate but important case: WiFi is the primary on-air connection mode in our data (83.3%). Even though the earliest versions of

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[6] *See generally Inquiry Concerning Deployment of Advanced Telecommunications Capability to All Americans in a Reasonable and Timely Fashion*, GN Docket No. 18-238, 2019 Broadband Deployment Report, 34 FCC Rcd 3857. https://docs.fcc.gov/public/attachments/FCC-19-44A1.pdf. (FCC 2019).

[7] *FCC 2019*, 34 FCC Rcd at 3873-3874, Fig. 2a; 3884, Fig. 11; 3901, Appx. 1; 4172, Appx. 7.

[8] *FCC 2019*, 34 FCC Rcd at 3874, Fig. 2b; 3901, Appx. 1.

[9] The newest on-air technological generation, 5G, was not available during the sample period, the second half of 2016. We therefore do not examine it in our study.

[10] The decision to focus on counties was due to the availability of American Community Survey (ACS) data at this level of aggregation. In addition, this level of aggregation protects consumer privacy in a way that an analysis at a smaller geographic level may not.

WiFi predate 3G, WiFi speeds are comparable to or often faster than LTE.[11] Counties with higher population density and counties with more minorities are more likely to have speed tests taken over older mobile technologies than over LTE or WiFi. This builds on previous research, which has shown that urban and minority consumers are becoming increasingly reliant on mobile broadband. The evidence of a mobile digital divide across economic dimensions is somewhat mixed; higher income and higher unemployment rates both lead to relatively more tests taken over WiFi. For tests that are taken over mobile technologies, both variables also lead to fewer tests taken over 3G, compared to both LTE and Non-LTE 4G. The existing infrastructure in a county also seems to have an effect. For example, counties with less wireline phone adoption are less likely to have tests taken over WiFi, and counties with more providers of a particular mobile technology are more likely to have tests taken over that technology.

With some notable exceptions, the nature of the mobile digital divide is similar when we examine download and upload speeds, as seen in Table 2. Population density is associated with faster speeds. Counties with higher minority populations seem to face slower speeds: a notable exception are counties with a higher proportion of African Americans, where speeds appear to be higher for some older mobile technologies. Speeds are faster in counties with higher median household incomes, but unemployment again has the opposite effect, with an increase in the unemployment rate being associated with slower mobile broadband speeds but faster WiFi speeds. The impact of infrastructure is mixed: lower wireline phone adoption is associated with lower speeds, while more competition seems to have a positive effect on older mobile technologies but have a negative effect for LTE or WiFi.

[11] Over time, WiFi speeds have increased due to improvements in WiFi technology and fixed broadband speeds. In addition, as mobile data use has steadily increased, network operators have increasingly focused on managing traffic volumes through data offloading with complementary technologies, such as WiFi. H. Zhou et al., *A Survey on Mobile Data Offloading Technologies*, 6 IEEE Access 5101, 5101 (2018).

Table 1: Summary of Technology Selection Regressions Results Relative to WiFi

Dependent Variable	*3G*	*Non-LTE 4G*	*LTE*
Population Density (Log)	-	-	-
Bachelors or More (%)			-
Other Race (%)			
Black or African American (%)	+	+	+
American Indian and Alaska Native (%)	+	+	+
Asian (%)	+	+	+
Hispanic or Latino (%)	+	+	+
Median Age (Log)	+	+	
Mean Travel Time (Log Minutes)	+		
Mean Household Size (Log)	-	-	-
Median Household Income (Log $)	-		
Unemployed (%)	-		
iOS	-	-	
Minimum Effective Radius	+		
No telephone service	+		
Log(1+Own Tech Provider Counts)		+	
Log(1+WiFi Provider Counts)			

"+" means at least 4 of the 6 month subsamples have at least a 10% statistically significant positive coefficient. "-" means the same for negative coefficients.

Table 2: Summary of Speed Regression Results

Dependent Variable		*3G*	*Non-LTE 4G*	*LTE*	*WiFi*
Population Density (Log)	*Download*	+	+	+	+
	Upload	+	+	+	+
Bachelors or More (%)	*Download*			+	
	Upload				+
Other Race (%)	*Download*		-		+
	Upload		-		+
Black or African American (%)	*Download*	+	+		
	Upload	+	+	+	
American Indian and Alaska Native (%)	*Download*		-	-	-
	Upload				-
Asian (%)	*Download*				-
	Upload				-
Hispanic or Latino (%)	*Download*	-		-	-
	Upload		+		-
Median Age (Log)	*Download*	-		+	-
	Upload	-	-	-	-
Mean Travel Time (Log Minutes)	*Download*	-	-		-
	Upload	-	-	-	-
Mean Household Size (Log)	*Download*			+	+
	Upload				+
Median Household Income (Log $)	*Download*	+	+		+
	Upload	+	+		+
Unemployed (%)	*Download*	-			+
	Upload	-		-	+
iOS	*Download*	+		+	+
	Upload	+		+	+
Minimum Effective Radius	*Download*				-
	Upload	-	-	-	
No telephone service	*Download*				-
	Upload				-
Log(1+Own Tech Provider Counts)	*Download*		+		-
	Upload	+	+	-	-

"+" means a 10% statistically significant positive coefficient. "-" means the same for negative coefficients.

2. Literature Review

Research interest in the digital divide precedes the widespread use of the term itself, with the most significant early study on the divide being the 1995 NTIA Report, "*Falling through the net: A survey of the "have nots" in rural and urban America,"* followed by two subsequent studies released over the next four years.[12] In these reports, the NTIA used U.S. Census Bureau data to demonstrate the lower penetration rates that certain demographics experienced regarding access to telephones, Internet, and personal computing, both in absolute terms and relative to other population groups. These reports highlighted deficiencies of service among rural and urban populations, racial minorities, young households and households with low educational attainment or income.[13]

Since then, a wide literature of academic, private and government research has developed, which studies the severity and nature of the digital divide in the United States. Much effort has been made to document which demographic groups are particularly disadvantaged by the divide, and how policy can target these groups more effectively. Hindman (2000) finds that income, education and age are stronger predictors of the digital divide than rural or urban status.[14] Based on data from the Pew Foundation, Chaudhuri, Flamm and Horrigan (2005) and Flamm and Chaudhuri (2007) find that income and education are important determinants of demand for Internet access and broadband.[15] Goldfarb and Prince (2008) find that wealthier Americans adopt Internet service more frequently but that once they gain access, poorer Americans are more likely to use the Internet.[16] Wilson, Wallin and Resier (2003), Prieger (2003), Prieger and Hu (2008) and Mossberger, Tolbert and Hamilton (2012) document disparities in access for and use by African Americans and Latinos relative to Whites.[17] Anderson and Perrin (2017) show using Pew data that more elderly are using smartphones and

[12] NTIA, *Falling through the net: A survey of the "have nots" in rural and urban America* (July 12, 1995), https://www.ntia.doc.gov/ntiahome/fallingthru.html. (NTIA 1995); NTIA, *Falling through the net II: New data on the digital divide* (July 28, 1998), https://www.ntia.doc.gov/files/ntia/publications/falling-through-net-ii.pdf (NTIA 1998); *NTIA 1999*.

[13] *See also* Government Accounting Office, *Characteristics and Choices of Internet Users*, GAO-01-345 (Feb. 2001), https://www.gao.gov/new.items/d01345.pdf. (GAO 2001).

[14] Douglas B. Hindman, *The rural-urban digital divide*, 77 Journalism & Mass Communication Quarterly 549 (2000). For a study of urban-rural digital divide in the United Kingdom, Lorna Philip et al., *The digital divide: Patterns, policy and scenarios for connecting the 'final few' in rural communities across Great Britain*, 54 Journal of Rural Studies 386 (2017).

[15] Anindya Chaudhuri et al., *An analysis of the determinants of internet access*, 29 Telecommunications Policy 731 (2005); and Kenneth Flamm and Anindya Chaudhuri, *An analysis of the determinants of broadband access*, 31 Telecommunications Policy 312 (2007).

[16] Avi Goldfarb & Jeff Prince, *Internet adoption and usage patterns are different: Implications for the digital divide*, 20 Information Economics and Policy 2 (2008).

[17] Kenneth R. Wilson et al., *Social stratification and the digital divide*, 21 Social Science Computer Review 133 (2003); James E. Prieger, *The supply side of the digital divide: Is there equal availability in the broadband Internet access market?*, 41 Economic Inquiry, 346 (2003); James E. Prieger, J. E., & Wei-Min Hu, *The broadband digital divide and the nexus of race, competition, and quality*, 20 Information economics and Policy, 150 (2008); and Karen Mossberger et al., *Broadband adoption: measuring digital citizenship: Mobile access and broadband*, 6 International Journal of Communication, 37 (2012).

the Internet, but still lag their younger peers on digital engagement on multiple dimensions.[18] Pearce and Rice (2013) examine how the digital divide is influenced by whether consumers are primarily able to access the Internet using mobile devices or using a computer.[19] Haight et al. (2014) looks at many aspects of the digital divide in Canada, with special emphasis on social networking sites.[20]

To our knowledge, the paper that is most related to ours is Riddlesden and Singleton (2014), which looked at crowdsourced fixed speed data in England.[21] Like us, they have access to speed test data, though in the form of a website (broadbandspeedchecker.co.uk), not a mobile app. The authors look at the impact of various geographic variables on speeds, with an emphasis on distance to exchanges. Like older studies with more traditional types of data, they find highly urban centers are better off as they have higher speeds. Unlike older studies, they find that speed does not strictly decrease with an index of socio-economic "deprivation."[22] Rather, there is a "U-Shaped relationship" with the lowest speeds measured in moderately deprived areas, and the highest speeds measured in the most deprived areas. The authors hypothesize that this is due to the fact that the urban poor live in very densely populated areas and coincidentally benefit from these areas' better buildouts.

Prieger (2013) is also closely related and studies the rural broadband digital divide, with an emphasis on mobile.[23] Using FCC, NTIA and U.S. Census Bureau Current Population Survey (CPS) data, Prieger found that rural areas have fewer mobile broadband providers but more slow fixed providers, even while mobile broadband helps "fill in" gaps in fixed rural service. Similar to Hindman (2000) and Wilson, et al. (2003),[24] he finds that the estimated broadband digital divide diminishes after controlling for demographics, although only mobile usage and not fixed usage, for which the divide remains. Unlike our study, Prieger lacks data on network quality so he can only speculate on that aspect of the mobile digital divide.

For our study, we use crowdsourced U.S. mobile data from Ookla, a major operator of speed tests worldwide. Economists have used Ookla data before: Rohman and Bohlin (2012,

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[18] Monica Anderson & Andrew Perrin, *Tech adoption climbs among older adults*, Pew Research Center (May 17, 2017), https://www.pewresearch.org/internet/2017/05/17/tech-adoption-climbs-among-older-adults/.

[19] Katy E. Pearce & Ronald E. Rice, *Digital divides from access to activities: Comparing mobile and personal computer Internet users*, 63 Journal of Communication 721 (2013).

[20] Michael Haight et al., *Revisiting the digital divide in Canada: The impact of demographic factors on access to the internet, level of online activity, and social networking site usage*, 17 Information, Communication & Society 503 (2014).

[21] Dean Riddlesden & Alex D. Singleton, *Broadband speed equity: A new digital divide?*, 52 Applied Geography, 25 (2014).

[22] Riddlesden & Singleton (2014) use the official UK Government indices of poor socio-economic well-being, the Indices of Multiple Deprivation. Riddlesden & Singleton, *supra* note 21, at 29.

[23] James E. Prieger, *The broadband digital divide and the economic benefits of mobile broadband for rural areas*, 37 Telecommunications Policy 483 (2013).

[24] Hindman, *supra* note 14; and Wilson, *supra* note 17.

2013) and Kongaut and Bohlin (2017) use Ookla tests blended between fixed and mobile to examine the impact of improved broadband quality on economic growth.[25]

Unlike previous studies, we focus exclusively on data from mobile devices. Measurement of mobile phone quality is more common in the computer science and engineering literatures than in economics or public policy, though in these fields such measurement is usually done for its own sake rather than to inform policy. Canadi et al. (2012) look at Ookla data measurements for fixed and mobile tests and compare them with tests of fixed speeds from the FCC's Measuring Broadband America initiative.[26] Schatz and Egger (2011) measure mobile broadband quality in Austria;[27] Chetty, et al. (2013) in South Africa;[28] and Awan, et al. (2015) and Arshad, et al. (2016) in Pakistan.[29]

With its focus on the mobile digital divide, our study fills a gap in the existing research. Previous studies focus mostly on questions of access or usage of fixed Internet as defining the digital divide. Given the differences in fixed and mobile technology, previously identified digital divides between rural and urban, rich and poor, and between races will not always agree with the results of our study. For example, a 2015 Pew Report notes that African Americans and Hispanic Americans are more likely to be dependent on mobile for broadband access – but it is possible that the speed of service can vary widely, even within the same mobile technology. As mobile technology continues to improve, and demand for mobile service increases, the importance of documenting the digital divide in the mobile Internet will only increase for policymakers.

3. Estimation

We estimate two separate models using the 2016 Ookla data. As discussed above, one model examines the selection of connection technology, while the other considers download and

[25] Ibrahaim K. Rohman, & Erik Bohlin, *Does broadband speed really matter for driving economic growth? Investigating OECD countries*, 5 International Journal of Management 2 (2012); Ibrahaim K. Rohman, & Erik Bohlin, *The impact of broadband speed on the household income: comparing OECD and Brics*, Working Paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2226899 (2013); and Chatcai Kongaut, & Erik Bohlin, *Impact of broadband speed on economic outputs: An empirical study of OECD countries*, 3 Economics and Business Review 12 (2017).

[26] Igor Canadi et al., *Revisiting broadband performance*, Proceedings of the 2012 Internet Measurement Conference 273 (2012).

[27] Raimund Schatz, & Sebastian Egger, *Vienna surfing: assessing mobile broadband quality in the field*, Proceedings of the first ACM SIGCOMM workshop on Measurements up the stack 19 (2011).

[28] Marshina Chetty et al., *Measuring broadband performance in South Africa*, Proceedings of the 4th Annual Symposium on Computing for Development 1 (2013).

[29] Muhammad F. Awan et al., *Measuring broadband access network performance in Pakistan: A comparative study*, 2015 IEEE 40th Local Computer Networks Conference Workshops (LCN Workshops) 595 (2015); and Tayyad Arshad et al., *Performance Evaluation of Mobile Broadband Cellular Networks in Pakistan*, 2016 IEEE 41st Conference on Local Computer Networks Workshops (LCN Workshops) 104 (2016).

upload speeds, with all outcome variables measured at the level of a "single" test.[30] Both analyses explore the relationship between: the respective outcome variables; factors that impact wireless broadband speed, service and availability at the scale of the county; and county level demographic information. County-level data are used because we are not able to relate any unique test with a known individual, however we are able to associate each observation with the county within which the test was run.[31] Tests are likely to happen outside the home, so using the demographic average of a county is like applying the expected demographic of the tester as a correction.[32] Therefore, the results should not be interpreted to provide information regarding the relationship between individual characteristics and the quality of service received. Instead, this analysis seeks to understand how county demographics and characteristics are related to the quality of service, measured by speed and technology generation, that is available in that county.

It is likely that some of the independent variables are endogenous to the outcome variables in these two estimations. Therefore, although these results demonstrate a direct relationship between the outcome variables and the regressors, they do not necessarily represent a causal relationship. In addition, the Ookla speed data does not allow us to observe whether the decision to use a certain technology is voluntary or involuntary (for example, whether the consumer actively decides to use mobile data versus WiFi versus the decision being a result of the default connection settings of their mobile phone).

3.1 Technology Selection by Conditional Multinomial Logit

To examine the digital divide in access across technologies, we use a conditional multinomial logit model to evaluate the relationship between county demographics and the probability of which technology generation (3G, Non-LTE 4G, LTE, or WiFi) a test runs on. Older technology generations are more likely to provide poorer service, and mobile service in

[30] Throughout the analysis, we account for users who may be over-represented in the data by aggregating all observations that have the same device, on-air technology generation (3G, LTE, Non-LTE 4G, and WiFi), carrier, county, and hour. Ookla data contains a Unique Device ID that allows us to identify the tests that are run by an individual user. Certain devices, identified by their Unique Device IDs, are over-represented in the data. It is possible that some tests are from users who have altered the source code of the Ookla Speedtest app, so that the test is automatic and does not require the user to manually initiate each test. It is important to account for this over-representation; however, we also do not want to eliminate these tests entirely because they may provide important information about temporal or spatial variations in speeds. In addition, if these tests are valid, we may introduce a different kind of selection effect if they are removed. In certain cases, it is difficult to determine whether a test should remain in the sample data set, or if it should be removed. As a compromise, and to generate a more representative sample, we replace tests that have multiple observations within a single user ID/technology/carrier/county/hour set as a single observation, consisting of the median speed of this sub-group of observations. The result of this transformation reduces our sample size from over 101 million observations to over 51 million observations.

[31] We did not attempt to determine the home location of a tester by analyzing their testing patterns. To be confident in the home estimation location would require large numbers of tests per tester, which would greatly reduce the sample. It would also bias the tests toward individuals who test a lot and who may be atypical. Finally, it is unclear what the best estimation technique for this process would be.

[32] There is trade-off: a smaller area is more likely to be biased but a larger area is more imprecise. Also, a better way to apply this correction would be to use zones of equal area, centered at the test point. We found counties to strike a balance in size and also be the most convenient geographic area, but counties vary in area and tests are never at the exact center of counties.

general has much slower speeds than WiFi.[33] If our analysis finds that some demographic dimension has a strong impact on the probability of testing on older generations or on mobile in general, this provides evidence that there is a digital divide in access along that dimension. In the multinomial logit model, the probability that a test runs on a given technology corresponds to the probability that a latent value for that technology is higher than the latent value for any other technology. Variables that have a strong impact on the latent value therefore have a strong impact on the probabilities. While the multinomial logit is often used to model active choice, we emphasize that we are using the multinomial logit to model the general probability of a test being run on one technology rather than another. This probability includes elements of active choice (handset model, carrier, optional device settings), as well as external constraints (network quality, network management practices, and internal device settings). It also may be the case that at least one technology is not available in a particular location for a particular test. To clarify that the process we model is comprised of more than active choice, we refer to this process as the "technology selection" rather than "technology choice."

Our specification for the latent value, $U_{i,Tech}$, for each technology generation is:

$$\begin{aligned} U_{i,Tech} = {} & \phi_{Hour,\,Tech} + \phi_{Carrier,\,Tech} + \phi_{State,\,Tech} + \ln(1 + ProviderCount)\,\gamma \\ & + \ln\left(1 + \,WiFiCount\,\gamma_{WiFi,Tech}\right)\gamma_{wifi} + \,X_{County}\,\alpha_{Tech} + Radius\,\alpha_{Radius,Tech} \\ & + iOS\,\alpha_{iOS,Tech} + \,\psi_{i,Tech} \end{aligned}$$

$\phi_{Hour,\,Tech}$ is an interaction between the hour of the day and the connection technology. This variable accounts for the possibility that consumers may vary their connection type depending on the time of day. For example, users of older technologies may have different usage patterns relative to users of new technologies, or consumers may access different connection technologies at home versus at work.

$\phi_{Carrier,\,Tech}$ is an interaction between the carrier and the connection technology. Carrier networks vary based on their how they implement their technology and how extensively such technology is deployed.

$\phi_{State,\,Tech}$ is a state and technology interaction term, which captures any state-specific variation, such as unique regulations by state public utility commissions, and state rules governing tower siting and rights of way.

$ProviderCount$ is the weighted mean of the number of mobile carriers that provide service within a given county. Specifically, this variable is the weighted mean number of carriers of a particular technology in each census block within a county, based on June 2016 FCC Form 477 data,[34] and weighted by the area of each census block. This weighted mean gives

[33] Mobile service does have some compensating value relative to WiFi. Mobile data has a much wider geographic range than WiFi, thus mobile data connections will be faster and more consistent than WiFi when the device is further from the source of the signal. However, when available, WiFi generally provides faster speeds and a more reliable connection than mobile. In addition, WiFi does not count towards the data cap that a mobile plan might have.

[34] Federal Communication Commission, *Mobile Deployment Form 477 Data*, https://www.fcc.gov/mobile-deployment-form-477-data (last visited December 22, 2020).

a general sense of the typical number of carriers within each technology generation that one could access at any given point in the county. Using the total number of mobile providers within the entire county would potentially overstate the availability of that technology, because it does not account for the footprint of each provider within that county. The value of this variable is specific to the technology of the option considered: the latent value for LTE will include the weighted mean of the number of LTE carriers, the latent value of Non-LTE 4G will include the weighted mean of the number of Non-LTE 4G carriers, and the latent value of 3G will include the weighted mean of the number of 3G carriers. We are normalizing WiFi as the reference option with a utility of zero, thus we include the analogously calculated weighted count of wireline Internet providers ($WiFiCount\ \gamma_{WiFi,Tech}$) in each latent value of the other options to account for the possibility that a consumer is more likely to use WiFi if it is more widely available.[35]

X_{County} is a vector of county characteristics, which includes the population density and mean travel time to work, and socioeconomic characteristics of the county, such as age and race of the population and median household income and size. If a variable is not a percentage, the variable is logged to reduce the skewness.

$Radius$ is the minimum effective radius of a tower in the county, which is an estimate of the distance at which a receiver can receive an effective signal from a particular cell tower. A larger radius should be correlated with higher speeds and a wider coverage area, which may influence consumers to use mobile data connections instead of WiFi. In previous work, the FCC assigned minimum effective radii to U.S. counties based on engineering estimates of transmission effectiveness in the terrain of those counties[36] – a more rugged terrain means the radius must be shorter, thus more cells are necessary for effective buildout.

$iOS\ \alpha_{iOS,Tech}$ is an iOS dummy, which is included because Apple technology may handle traffic differently than Android technology, both on a hardware and a software basis.

Finally, $\psi_{i,Tech}$ is unobserved variation specific to each test and technology generation. We assume it is distributed as type 1 extreme value, leading to the logit specification for probabilities. This allows an analytical form for the log likelihood of the observed technologies used, which we then optimize in maximum likelihood estimation.

3.2 Speed Regressions by OLS

Our second model examines how speeds relate to technological and county characteristics. We identify which tests were run on each technology and divide the data into

[35] We use FCC Form 477 data for fixed broadband to develop the analogous measure for WiFi. Federal Communication Commission, *Fixed Broadband Deployment Data from FCC Form 477*, https://www.fcc.gov/general/broadband-deployment-data-fcc-form-477 (last visited December 9, 2020).

[36] The radius is discretized into four levels – 2, 3, 5, and 8 miles – in the current paper we use the untransformed radius with floor at 2 miles and a ceiling of 8 miles. FCC, *The Broadband Availability Gap: OBI Technical Paper No. 1*, at 68-72 (Apr. 2010), https://transition.fcc.gov/national-broadband-plan/broadband-availability-gap-paper.pdf (FCC 2010).

subgroups based on this classification, then run separate OLS regressions of log upload and log download speed, in kbps, on the same variables used to investigate our first question. [37]

Our specification for the regression on speed, $speed_{i,tech}$, closely parallels the specification of the technology access equation in terms of included covariates:

$$\ln\left(1 + speed_{i,tech}\right) = \theta_{Hour,\,Tech} + \theta_{Carrier,\,Tech} + \theta_{State,\,Tech} + \ln\left(1 + ProviderCount_{Tech,County}\right)\zeta + X_{County}\beta_{Tech} + Radius\ \beta_{Radius,Tech} + iOS\ \beta_{iOS,Tech} + \epsilon_{i,Tech}$$

We use logarithm of download and upload speeds as the dependent variable to dampen the extreme skewness in speeds and add the 1 to ensure that the argument of the log function is never zero, which would otherwise be the case in a few observations. Since 1 kbps is relatively small compared to the average speed (*X*), this has little effect on the final results, and we avoid having to drop otherwise valuable observations. A major difference between this specification and the logit is the lack of a reference option, so we do not include the WiFi provider count in any regression done on subsamples besides the WiFi subsample. For the WiFi subsample, the WiFi provider count naturally appears as the own provider count.

4. Data

4.1 Data Overview

Our analysis combines Android and iPhone Ookla data from the second half of 2016, with county-level census data, cell-size radius, and other county-level characteristics. The Ookla Speedtest mobile app measures network quality as experienced on individual smartphones and other mobile devices,[38] and is available free of charge for iOS, Amazon, Android, and Windows Phones. Data collected via the Ookla Speedtest app is solely crowdsourced and requires users to choose to run each individual test.[39] A test may reflect a WiFi or a mobile network connection,

[37] One could potentially argue that consumers choose their connection technology based on the speeds they would like to experience and speculate that if speeds are explained by unobserved heterogeneity of users, the second portion of our analysis may feed into the first. However, we assume that the connection type is directly related to the availability of the different technology generations in a particular county.

[38] Speedtest, *Ookla Speedtest Apps for Mobile*, http://www.speedtest.net/mobile/ (last visited Dec. 9, 2020).

[39] Various methodologies are used to measure mobile network speeds. The two most prevalent rely on crowdsourced data or structured sample data. Crowdsourced mobile speed data are user-generated data produced by consumers who voluntarily download speed test applications on their mobile devices. Generally, crowdsourced data can bring the benefits of generating a large volume of data at a very low cost, and of measuring actual consumer experience on a network in a wide variety of locations, both indoor and outdoor. We note, however, that crowdsourced data are often not collected pursuant to statistical sampling techniques and may require adjustments to construct a representative sample from the raw data. For instance, crowdsourced mobile data come from a self-selected group of users, and there often is little control regarding such parameters as when people implement the test, whether the test is performed indoors or outdoors, the geographic location of the tester, and the vintage of the consumer's device. Structured sample data, by contrast, are generated from tests that control for the location and time of the tests as well as for the devices used in the test. Structured sample data may be collected using stationary

based on the current connection status of the mobile device.[40] Ookla collects and reports similar but different variable sets for the various operating systems. The Ookla variables that are used in our analysis include: a unique test ID, the date and time of the test, download and upload speeds, the latitude and longitude of the device at the time of the test, provider name and provider code, connection technology, and other miscellaneous variables.[41]

Each wireless network can be identified using a combination of the "operator name" and a unique "operator code." This information can be collected from the network itself, and in the case of Android phones, is also available via the SIM card. However, this data set is not always perfect. An operator name may be misspelled, an operator code may be incomplete, and it is also possible that one or both fields could be missing. In some cases, the owner of a mobile device may have altered the information on the SIM card, although this only occurs in a very small percentage of the sample. To assign the appropriate network operator to each test, we first cleaned and normalized all name and code fields. Then, based on conversations with the various providers, we identified the operator codes that are associated with each primary brand, as well as the codes that are associated with any affiliate brands.[42] This paper only specifically considers the primary brand and an aggregate of the affiliate brands of AT&T, Verizon, T-Mobile, and US Cellular, with all remaining carriers categorized as "Other." The name assignment rules are presented in detail in Appendix A.

We are able to identify the county in which each test was performed by mapping the latitude and longitude of the test.[43] Any observation that was not located within a county, as

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indoor or outdoor tests, or drive tests. However, these tests are more expensive to conduct, involve significant judgment about when and where the tests are run, often involve insufficient testing at indoor locations or in many rural areas, and typically produce datasets that are not as rich as crowdsourced data–all of which are likely to have some effects on reported results.

[40] While Ookla is one of the most prominent providers of crowdsourced data, the FCC has also made available a mobile app that gathers such data. FCC, *Measuring Mobile Broadband*, https://www.fcc.gov/general/measuring-mobile-broadband-performance (last visited Dec. 9, 2020). RootMetrics publishes broadband performance metrics that are largely based on drive test data in across the U.S., but also incorporate results of some crowdsourced data. RootMetrics, *Connected Insights for Your Connected Lifestyle*, http://www.rootmetrics.com/en-US/home (last visited Dec. 9, 2020). The California Public Utilities Commission's CalSPEED project measures mobile network speeds in California based primarily on a structured sampling scheme. California Public Utilities Commission, *Mobile Broadband Testing*, http://www.cpuc.ca.gov/General.aspx?id=1778 (last visited Dec. 9, 2020). Speed measurements are also performed by other entities besides those listed above.

[41] For more details, *See* Speedtest, *Speedtest Support*, https://help.speedtest.net/hc/en-us (last visited Dec. 9, 2020).

[42] For example, although Cricket is an affiliate brand of AT&T and operates over the AT&T network, Cricket sets a cap for the maximum possible download speed that a user can experience. Therefore, it is important to separate the speeds measured over affiliate brands from those measured over flagship brands.

[43] Ookla assigns the location of the test in two ways. First, if GPS is turned on in the mobile device, and is available at a location, then a precise latitude and longitude is recorded which reflects the exact location of the mobile device at the time of the test. If the GPS is not turned on or is not available, then the location is identified using IP geolocation (GeoIP). *See* Speedtest, *How does Ookla determine ISP names? How can I change this information?*, https://support.ookla.com/hc/en-us/articles/234578348-How-does-Ookla-determine-ISP-names-How-can-I-change-this-information-, (last visited Dec. 9, 2020). In the cases for which GeoIP does not identify a known location, the default location that is given is located in FIPS code 20155, which is associated with Reno County, Kansas. To prevent the false assignment of tests to this location, we drop any test for which the location was identified using GeoIP, and also any test that maps to FIPS code 20155.

defined in the 2010 Census, was dropped from the data set.[44] Based on the associated county FIPS codes, we assigned demographic data from the US Census Bureau's Five-Year estimates from the American Community Survey (ACS), as well as other county-level characteristics. The ACS collects data annually from a random sample of Americans to supplement the fuller data collection of the Decennial Census. Since the ACS is a sample, the results are an estimate of the population statistics, so we use the five-year estimates, which include data from 2010 to 2015, for more precision.[45]

We include county-level demographic variables in order to focus on the social and economic dimensions across which the digital divide is thought to lie. The 2010 Census population density is included; it is likely that a higher population density will lead to greater investment in equipment by firms, since it is more profitable for a wireless company to build a network in a county with more potential customers residing in a given land area. For other demographic variables, we turn to the 2015 five-year ACS. We use race and ethnicity variables as a fraction of the total population, since the access to and quality of broadband has been noted to be worse for African American and Hispanic American populations. We also include the median age of the population. Further, we include from the ACS the county-level adoption rate of wireline telephone service to investigate the link between wireline adoption and wireless quality.[46]

According to the aforementioned literature on the digital divide between rich and poor, wealthier consumers are more likely to afford and use broadband service. Thus, we propose that wealthier counties are more likely to attract investment and buildout by broadband providers. To examine this proposal, we include county-level median household income. In addition, we use the unemployment rate, which is defined as the percent of the labor force unemployed.[47] We include the percentage of the population with a bachelor's degree or higher, since a more educated populace might demand higher quality mobile broadband.

We control for differences in "rush hours" across technology types by including on-air technology-hour interactions. We expect that congestion causes speeds to be relatively slower during the day and relatively faster overnight. Finally, to account for the differences in access across counties and for different technologies, we use both fixed and mobile FCC Form 477 data

[44] ACS data are not available for territories; thus, our analysis is further restricted to those tests taken within states. In addition, some data is taken at sea, so those observations are also dropped. In addition, some observations fall outside of the county map, but are in US waters, such as lakes, rivers, and coastal areas. These observations are also dropped from the analysis.

[45] ACS is based on the latest county definitions, and we assigned county FIPS codes to the Ookla data using the 2010 definitions. Some county designations were not identical between the two time periods. While many changes were simply changes in FIPS codes, some were more complicated. In the case where two counties were merged, the ACS data for the new county was assigned to all original counties. Any other changes are more complicated and have less obvious solutions, so tests in those counties were dropped from the data.

[46] There could be a correlation between wireline phone adoption and WiFi adoption, though this aspect would be also picked up by the WiFi provider count variable.

[47] Not in the labor force consists mainly of students, housewives, retired workers, seasonal workers interviewed in an off season who were not looking for work, institutionalized people, and people doing only incidental unpaid family work (less than 15 hours during the reference week). United States Census, *Glossary*, https://www.census.gov/glossary/#term_Notinlaborforce (last visited Dec. 9, 2020).

to account for the number of fixed and wireless providers in each county.[48] In counties with more providers of a technology, that technology may be easier to access and competition may make prices for those services lower. In addition, competition may make quality higher, which may manifest in higher speeds. Wallsten and Mallahan (2010) find this pattern in FCC data for the highest residential broadband speeds.[49]

4.2 Stylized Facts

After cleaning and filtering the data, the resulting sample contains approximately 50.5 million observations. Despite the non-random nature of crowd-sourcing, the speed tests in our sample are distributed geographically in proportion to the population. This is demonstrated in the plot of county population versus test totals in Figure 1 (the regression of this data has an R^2 of 0.95),[50] and can also be seen in Map 1 (Map of Tests), which for visual clarity shows only parts of the New England and Mid-Atlantic areas of the U.S.

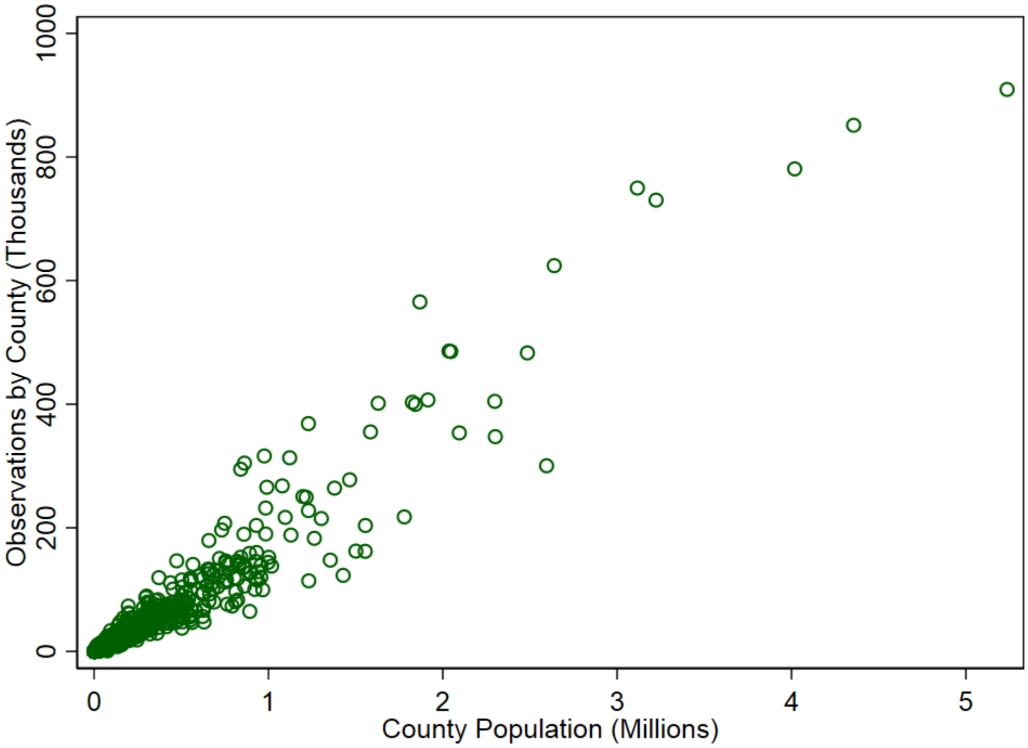
One of the most notable characteristics of the Ookla data is the extreme skewness of the measured speeds, which can be seen in Appendix Table B.3. Within our sample the mean speed always exceeds the median speed, often by a significant margin. For all technologies, the standard deviation is larger than the mean for both download and upload speeds. For example, the WiFi median download speed of 26.7 Mbps is much smaller than the 42.5 Mbps mean, which is itself smaller than the 284.8 Mbps standard deviation. This translates into WiFi download speeds having a skewness of 5,964.2. Such skewness is a challenge for regression analysis; thus, we prefer the median over the mean in this analysis and use logs of the variables when appropriate.

[48] *See* FCC, *Fixed Broadband Deployment Data from FCC Form 477*, https://www.fcc.gov/general/broadband-deployment-data-fcc-form-477 (last visited Dec. 9, 2020). Currently, all facilities-based broadband providers are required to file data with the FCC twice a year (FCC Form 477) on where they offer Internet access service at speeds exceeding 200 kbps in at least one direction. Fixed providers file lists of census blocks in which they offer service to at least one location, with additional information about the service. Mobile providers file maps of their coverage areas for each broadband technology (e.g., EV-DO, HSPA, LTE).

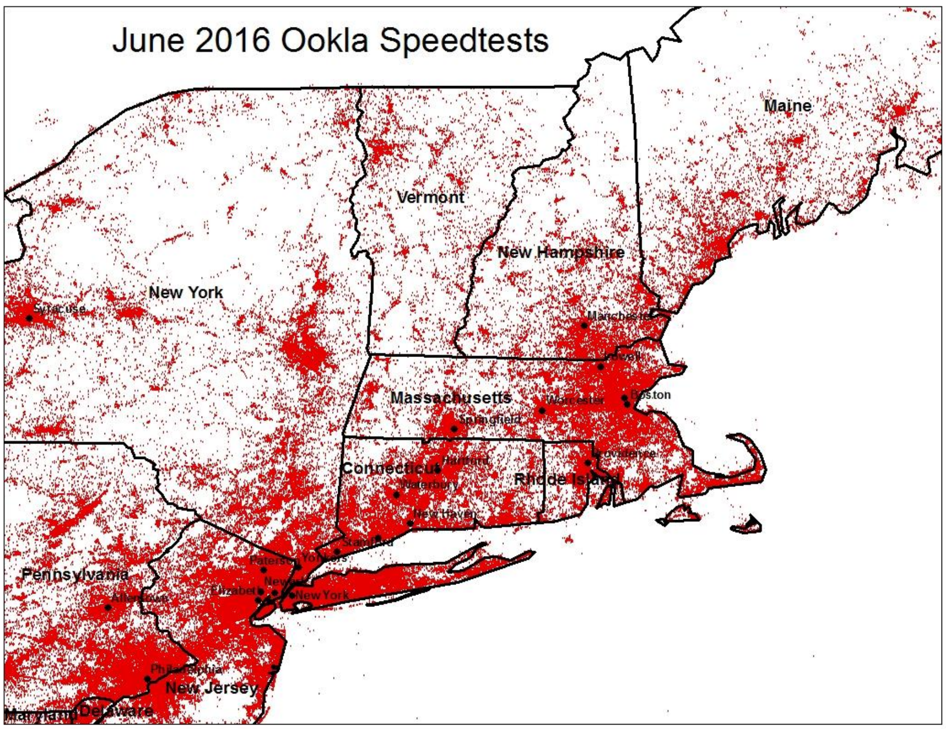
[49] Scott Wallsten & Colleen Mallahan. *Residential broadband competition in the United States*, Working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1684236 (2010).

[50] For readability, Figure 1 does not include Los Angeles county. Los Angeles county has a population of more than 10 million, almost twice as large as the next largest county. Despite this modification, the data set included in the Figure still results in a high R^2 of 0.93. Our regressions only use log population as a covariate so Los Angeles should not act as an outlier in the analysis.

Figure 1



Map 1



Appendix Tables II.1 and II.2 present the sample broken out by carrier and technology generation. We have classified any provider that is not one of the four nationwide providers or their affiliates, or US Cellular, as "Other."[51] The greatest proportion of tests are taken over WiFi (83.79% of tests), followed by LTE (15.05%), Non-LTE 4G (0.60%) and then 3G (0.56%). This is an unusually large amount of WiFi relative to outside estimates of how much total mobile traffic is generally carried over WiFi.[52] Each of the four nationwide wireless carriers appear in the sample at a rate that roughly reflects their national market shares.[53] AT&T and Verizon each represent over a quarter of the total number of observations, Sprint makes up less than 10% of the observations, and T-Mobile less than 20% of all observations.

With regards to the operating system, approximately 58% of tests taken are on iOS phones, approximately 42% are taken on Android, and the less than 1% remaining are taken on Amazon and Windows phones. Only Android and iOS tests are included in our analysis.

Appendix Table B.3 presents the distribution of download and upload speeds by technology. As expected, speeds increase with technology generation, and WiFi speeds are faster than mobile data speeds. This is consistent with intuition: newer mobile technologies are more efficient than old technologies, and WiFi data transfers primarily occur across fixed connections. Specifically, 3G data connections have a median download speed of 1.9 Mbps, Non-LTE 4G connections have a median download speed of 3.8 Mbps, LTE has a median download speed of 13.7 Mbps, and WiFi has a median download speed of 26.7 Mbps.

Geographically, a strong urban-rural split in speeds is hard to spot visually. As an example, Maps 2 and 3 display the choropleth of median LTE download and upload speeds at the county level. The areas with the slowest speeds are rural, and are especially likely to be remote, mountainous or desert regions. However, it is unclear if highly populated urban areas have the fastest speeds overall.

Given that there is not an obvious relationship between geography and mobile broadband speed, we posit that demographic variables may better explain variations in speed. To that end, Appendix Tables B.4 and B.5 present the correlation between demographic variables and the log download and upload speeds, either with speeds at the individual test level or county median speeds. Here, correlations with any of the explanatory variables are relatively low, with no correlation above 0.25 in magnitude. Therefore, the multivariate regression analysis will be especially valuable here as it will allow us to separate the complex interactions between the

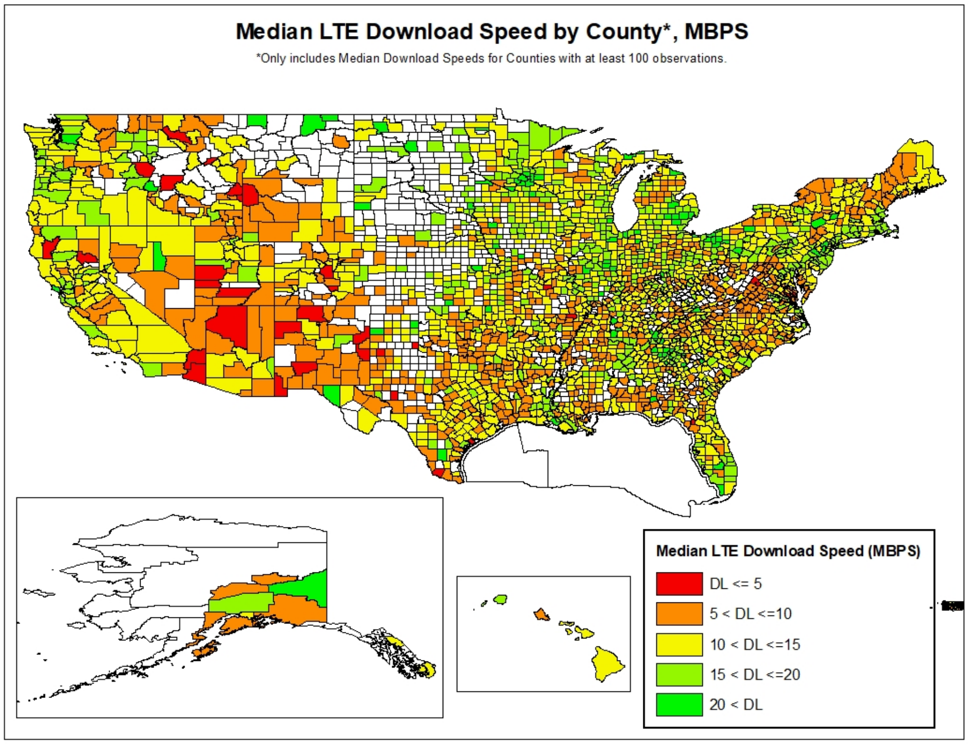
[51] Service providers each have their primary flagship brand, which is immediately recognizable to the public. In addition, among the four nationwide providers, AT&T, Sprint, and T-Mobile also market major discount brands. For example, AT&T also provides service under the name Cricket Wireless, Sprint also provides service under the name Boost Mobile, and T-Mobile also provides service under the name MetroPCS. These affiliate brands are cheaper, and generally have more restrictions on the maximum speeds, technology generations, and devices that are available to consumers.

[52] Cisco, *Cisco Visual Networking Index: Forecast and Trends, 2017–2022*. White Paper. (November 27, 2018), https://newsroom.cisco.com/press-release-content?articleId=1955935.

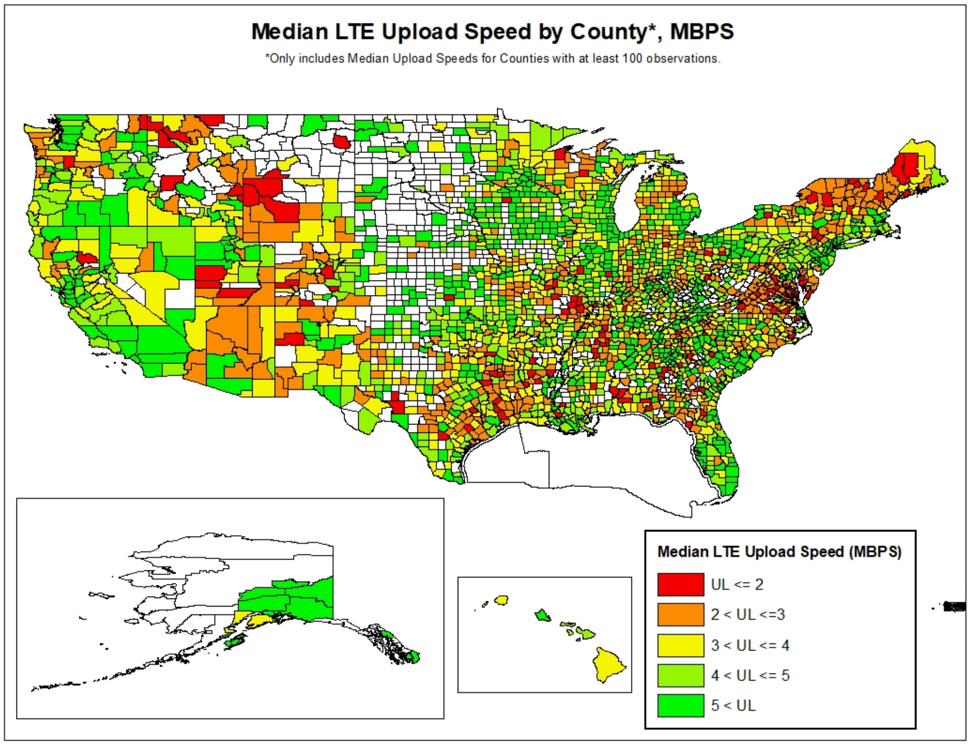
[53] In 2016, UBS Investment Research estimates that at the end of year 2016, Verizon had 35% market share, AT&T 32.4%, T-Mobile 17.1% and Sprint 14.3%. UBS US Wireless 411, Version 51, Table 21 (UBS 2014); UBS US Wireless 411, Version 59, Fig. 53 (UBS 2016); and UBS US Wireless 411, Feb. 2017, Fig. 33 (UBS 2017).

variables to a certain extent. The number of tests and speeds vary significantly over time, and reflect significant congestion effects, which is explored with our extensive use of time effects.

Map 2



Map 3



5. Results

The following section presents the results of the two research questions explored in this paper. First, we discuss the results of the multinomial logit on county demographics and characteristics, and technological variables, which explores the variation of technology connections across counties. We then consider the results of the OLS regressions of log download and upload speeds, which explore whether and how mobile broadband speed varies across counties. For the sake of brevity, we only explore the most pertinent results here—detailed results are presented in Appendix C.

5.1. Technology Selection Results

Due to the abundance of data, we faced computational constraints while running the logit. To make computation feasible, we ran our estimation of the multinomial logit model separately for each of the six months represented in our data. Each monthly subsample contains between 7.8 million to 9.1 million observations. Coefficients are estimated relative to the selection of WiFi as the connection technology, so a positive coefficient indicates that a variable increases the probability of selection of the technology relative to WiFi, and a negative coefficient indicates that a variable decreases this probability. Results are very similar across all months, and there are no obvious signs of seasonality. For the rest of this section, we refer to the results for all six months in general and note when a particular month has an unusual coefficient value. Further, the MLE coefficients for the multinomial logit model do not represent the marginal impact on the likelihood of an alternative due to the nonlinearity of the probability function. Given the difficulty of computing such impacts with our large data set, and some ambiguity on which particular marginal change calculation is most informative, we decline producing estimates here. However, the coefficients for the logged covariates are roughly the same magnitude as the corresponding percentage of the probability of a technology on a 1% of the unlogged covariate (elasticity of probability on the covariate),[54] while the coefficients of the percentage covariates are the same for the percentage change of probability of a technology over an increase of that covariate equal to 1% of the total population.[55]

[54] For simplicity, let us focus on a single county. Let $P_i(ln(x))$ represents our model's probability of a technology based on a logged covariate, x, specific to observation i, so that total county share of that technology is $\int P_i di$. The elasticity of the share of that technology on x is equal to $\frac{\int \frac{\partial P_i}{\partial x} di}{\int P_i di}$. Let β be the coefficient on $ln(x)$; the logit implies $\frac{\partial P_i}{\partial x} = P_i(1 - P_i)\frac{\beta}{x}$, so the elasticity is $\beta \frac{\int P_i(1-P_i)\, di}{\int P_i di}$ When P_i is small, then the integral is close to 1 and the elasticity is close to β. Given the very small shares of 3G and Non-LTE 4G, and the modest share of LTE, the model estimates similar small probabilities of these options. However, there could be significant deviation given variation in the data, especially across counties, and some variables are actually log of the variable plus one, which would introduce additional deviations from the derived formulas.

[55] We adopt the same assumptions of the derivation of the elasticity of probability on logged variables, except assume the percentage covariate x enters directly into the probability function. *Supra,* note 54. Without logging, $\frac{\partial P_i}{\partial x} = P_i(1 - P_i)\beta$. The percent change of the share of the technology in question over a marginal change in x is then $\beta \frac{\int P_i(1-P_i)\, di}{\int P_i di}$, which is again close to β when P_i is small. β is not comparable to an elasticity because we do not divide by x, so β cannot be interpreted as being the percentage change of P_i over a percentage change of x.

The multinomial logit estimates show that population density plays a modest role in technology selection across mobile connection technology generations. As seen in Table C.2, this variable has a small but significant effect in determining technology type. The effect for LTE seems to be close to zero, the effect for Non-LTE 4G approaches -0.2, and the effect for 3G is between -0.2 to -0.3. While small, *the pattern* of our results is consistent with previous strong correlations between population density and adoption of newer technologies. In addition, an increase in mean travel time to work[56] significantly increases the probability of using 3G, with coefficients for the other technologies relatively small and statistically insignificant. With more commuting time one might have expected more demand overall for all mobile technologies, not just 3G. Even so, these coefficients are generally supportive of the idea that consumers in urban or suburban areas with larger and denser populations are more likely to use WiFi or LTE to connect their mobile devices compared to consumers in more remote rural areas.

The coefficients on percentage of bachelor's or higher degree holders are all negative for 3G and LTE but are only statistically significant for LTE for five of the six months of data. Negative coefficients are consistent with the hypothesis that higher levels of education are associated with greater WiFi access, and lower levels of education are associated with a dependence on mobile broadband. Given the lack of statistical significance for most of the results, and that the results for Non-LTE 4G have positive and negative coefficients, this is only weak evidence for a connection between education and technology use.

According to the estimated coefficients, tests in counties with higher percentages of racial minorities are more likely to be taken using mobile data connections and are less likely to be taken over WiFi. In particular, tests taken in counties with relatively higher African American, Native American, Asian American and Hispanic or Latino populations are more likely to occur via mobile data. For African American, Native American and Hispanic or Latino percentages, the same pattern is seen: the highest coefficient is for the 4G Non-LTE, then 3G and then LTE. For Asian American percentage, LTE has the lowest coefficient across all months, but whether the coefficient for 3G or Non-LTE 4G is higher depends on the month. These results are consistent with the idea that these populations have less access to LTE and WiFi, and therefore rely on older technologies.

Results for the other social demographics are also relatively intuitive. The age coefficients imply that counties with older populations are modestly more likely to use 3G or Non-LTE 4G. However, the coefficients are not statistically significant for 3G for two months in the sample. In contrast, there is no statistically significant effect of age on LTE use. Mean household size has a strong effect on the likelihood of mobile technology selection, though less so for LTE compared to 3G and Non-LTE 4G. This is consistent with families relying more on fixed connections compared to mobile.

Rather, β is comparable to the percentage change of P_i over an increase of x equal to 1% of the county total, e.g. if x=50%, this is a change from 50% to 51% rather than 50% + (1% of 50%) = 50.5%. Again, this change is not likely to be exactly equal to the population average since the data has significant variation across observations, especially counties.

[56] Mean travel time to work is the average travel time in minutes reported to the U.S. Census Bureau by workers over 16 years old.

The impact of economic variables, presented in Table C.3, are somewhat mixed and difficult to interpret, particularly given the prior that more economically well-off consumers would use more advanced technology. For both variables, coefficients for Non-LTE 4G and LTE are generally negative but imprecisely estimated, and their values vary from month to month, but both variables have coefficients for 3G that are negative and statistically significant. The small negative 3G coefficients on median household income are consistent with the idea that richer populations are less likely to use an older technology. However, unemployment has very large and statistically significant coefficients for 3G, between -3.59 and -6.70. This suggests that counties with a higher unemployment rates are much less likely to use 3G compared to counties in which more of the population is employed, and it runs counter to the conclusion that income increases technology access.

The technological and access variables show some influence on technology use. The statistically significant negative coefficient on the iOS indicator implies that iOS users are more likely to be near or use a WiFi connection, compared to Android users.[57] The minimum radius variable seems to have little effect on technology selection. The effect of the percentage of homes without a landline telephone is always positive, though not statistically significant for some months, weakly suggesting that less landline phone adoption is correlated with less WiFi usage, which is based on fixed Internet service. In line with the idea that more competition means more adoption, the log count of mobile providers has positive and statistically significant coefficients for all months. In contrast, the measures of WiFi providers generally do not have much of an effect.

5.2 Speed Results

We now turn to the results of the OLS regressions of log download and upload speeds. Unlike the technology use results, we analyze all six months together, since OLS is not as computationally demanding as the logit. Download and upload speeds are analyzed separately, and the analyses are further segmented by technology. Coefficients on the log variables represent the percentage by which speed would increase with a 1% increase of the unlogged covariate (the elasticity). Coefficients on fractional variables represent the percentage by which speed would increase with increase of the covariate equal to 1% of the total population. Conditional on technology, both sets of regressions have broadly similar results, and so we report on both generally, noting differences when they occur.

Examining population density and travel time, we see a similar outcome to the technology use analysis. The population density coefficients, presented in Table C.15, are positive and statistically significant, but small in magnitude. Similarly, the coefficients on mean travel time are statistically significant and negative. These results imply that speeds are higher in densely populated urban centers, and slower in more remote, rural areas.[58] If we pair this with our previous conclusion that more urban counties have access to more recent connection technologies, it provides evidence of a rural/urban mobile digital divide.

[57] No non-LTE 4G tests are taken over iOs devices.

[58] As increasing commuting time might increase demand for higher speeds, the mean travel time coefficients are consistent with speeds being improved to respond to demand.

However, we cannot draw such clear conclusions on the relationship between education and speed of service. The only positive and statistically significant coefficients on the percentage of the population in a county that holds a bachelor's degree or higher are for LTE download speed and WiFi upload speed, and the remaining coefficients from this variable vary substantially and are not statistically significant.

We find that counties with relatively higher African American populations tend to experience higher mobile speeds for 3G and non-LTE 4G. The coefficients are modest but statistically significant for both download and upload tests. On the other hand, the evidence for LTE and WiFi is mixed: the coefficients for download tests for both are statistically insignificant and negative, while only the coefficient for LTE upload tests is statistically significant and positive. We combine these results with the suggestion in Riddlesden and Singleton (2014) that socially disadvantaged groups are disproportionately located in cities and thus paradoxically enjoy better speeds, and highly African American counties may be disproportionately located in urban markets with better profit incentives for buildout.[59] However, the correlation of population density and percentage of African Americans for counties in our sample is not high, 0.25, so the connection is not clear. In addition, the effect is stronger for older technologies, thus it is possible that the focus in these areas may be to maintain existing infrastructure, but not invest in updated technologies.

In contrast, the fraction of Native Americans in a county has a consistent significant negative effect on download speeds, with the exception of 3G download speeds, for which the coefficient is negative but insignificant. Similarly, the upload speed coefficients are negative but statistically insignificant for all connection technologies except WiFi, which is negative and statistically significant. These results imply that wireless infrastructure on Tribal lands is not often updated, leading these populations to be poorly served.

The coefficients on Asian population percentage are only statistically significant for WiFi, but both download and upload tests have large, negative coefficients. As Asian population percentage is modestly correlated with population density on a county level (0.40), this is weak evidence against the idea of urban minority populations could enjoy better service, as in Riddlesden and Singleton (2014).

The effects of the relative percent of Hispanic residents in a county are not straightforward – the coefficients are negative (although statistically insignificant for non-LTE 4G) for download mobile speeds, but positive for upload mobile speeds, except for WiFi.

Median age has negative, statistically significant coefficients for almost all regressions, except for the LTE download tests regression, which is positive and significant, and the non-LTE 4G tests regression, which is statistically insignificant. Negative coefficients are consistent with older populations having slower service, but there is not an obvious reason why the LTE download coefficient is positive.

Mean household size has positive and statistically significant coefficients for both WiFi download and upload tests, but the results are much more mixed for mobile technologies, with

[59] Riddlesden & Singleton, *supra* note 22.

only the coefficient for LTE download tests being statistically significant. The fact that speed is faster for counties with larger households might be endogenous to the reason that these same counties are more likely to use WiFi: firms might build faster fixed networks in residential areas with more WiFi usage.

Similar to the technology selection analysis results, the economic variables in Table C.16 yield somewhat mixed results. Median income coefficients are positive and significant for download and upload speeds in each technology subsample, with the exception of the LTE coefficients, which are positive and not statistically significant. These results are consistent with counties in better economic condition having better service. In direct contrast, the WiFi coefficient for unemployment percentage are positive and statistically significant, so that speeds appear to increase with the rate of unemployment. The evidence is further mixed for LTE: the unemployment coefficient for LTE download is positive and for LTE upload is negative. The unemployment coefficients for 3G are negative and significant, and the 4G coefficients are negative and not statistically significant.

Technology and infrastructure appear to have a complex effect on speeds. The statistically significant iOS coefficients are positive for 3G, negative for WiFi, and mixed for LTE. Thus, the effect iOS devices have on speeds is unclear. Minimum effective radius appears to have unexpected and small impact on speeds – all associated coefficients are negative, meaning that flat and uncluttered terrain leads to slower speeds. The percent of homes without telephone adoption has a more expected result, with negative coefficients for all samples. These negative results are only statistically significant for the WiFi coefficients, which may imply that speeds of the wireline broadband services used to support WiFi are correlated with wireline phone service.

Finally, we have a mixed impact of provider count: both 3G and non-LTE 4G have positive coefficients, but LTE and WiFi, have negative coefficients. Positive provider count coefficients are consistent with greater quality accompanying competition, so the negative coefficients for the higher speed technologies are odd. One possible explanation is that higher speed technologies might have a greater return for additional investment compared to older mobile technologies that cannot be improved much.

6. Conclusion

With its focus on the mobile digital divide, this paper adds to the literature, and generally provides a more complete understanding of how different groups access the internet. Overall, we conclude that the mobile digital divide does exist across certain dimensions. However, the results suggest that there is not a digital divide across other dimensions in our study. In addition, the mobile "have-nots" do not always line up with the fixed "have-nots." There is modest evidence that rural areas are more dependent on non-WiFi mobile technology and experience slower speeds on their mobile connections. The data are consistent with previous findings of a mobile digital divide across race with minorities more likely to use older mobile technologies and experience slower speeds. Counties with older populations are more likely to use mobile technologies and are more likely to have slower speeds. Counties with larger households are more likely to use WiFi and also have faster WiFi. The indicators of economic health of the county are mixed, with higher income counties and counties with higher levels of unemployment both seeming more likely to use WiFi and have faster speeds. Technological and infrastructure related variables also appear to have mixed and complicated effects. In particular, consumers in counties with more providers of a particular technology are more likely to use that technology, but the impact on speed depends on the technology. These complex and sometime counter-intuitive effects suggest that future research and on-the-ground data are necessary to further examine the nature of the mobile digital divide.

7. References

Monica Anderson & Andrew Perrin, *Tech adoption climbs among older adults*, Pew Research Center (May 17, 2017), https://www.pewresearch.org/internet/2017/05/17/tech-adoption-climbs-among-older-adults/.

Tayyad Arshad et al., *Performance Evaluation of Mobile Broadband Cellular Networks in Pakistan*, 2016 IEEE 41st Conference on Local Computer Networks Workshops (LCN Workshops) 104 (2016).

Muhammad F. Awan et al., *Measuring broadband access network performance in Pakistan: A comparative study*, 2015 IEEE 40th Local Computer Networks Conference Workshops (LCN Workshops) 595 (2015).

Igor Canadi et al., *Revisiting broadband performance*, Proceedings of the 2012 Internet Measurement Conference 273 (2012).

Anindya Chaudhuri et al., *An analysis of the determinants of internet access*, 29 Telecommunications Policy 731 (2005).

California Public Utilities Commission, *Mobile Broadband Testing*, http://www.cpuc.ca.gov/General.aspx?id=1778 (last visited Dec. 9, 2020).

Marshina Chetty et al., *Measuring broadband performance in South Africa*, Proceedings of the 4th Annual Symposium on Computing for Development 1 (2013).

Federal Communications Commission, *Inquiry Concerning Deployment of Advanced Telecommunications Capability to All Americans in a Reasonable and Timely Fashion*, GN Docket No. 18-238, 2019 Broadband Deployment Report, 34 FCC Rcd 3857. https://docs.fcc.gov/public/attachments/FCC-19-44A1.pdf.

Federal Communications Commission, *Bridging the Digital Divide for All Americans*, https://www.fcc.gov/about-fcc/fcc-initiatives/bridging-digital-divide-all-americans (last visited Dec. 9, 2020).

Federal Communications Commission, *Fixed Broadband Deployment Data from FCC Form 477*, https://www.fcc.gov/general/broadband-deployment-data-fcc-form-477 (last visited Dec. 9, 2020).

Federal Communications Commission, *Measuring Mobile Broadband*, https://www.fcc.gov/general/measuring-mobile-broadband-performance (last visited Dec. 9, 2020).

Federal Communication Commission, *Mobile Deployment Form 477 Data*, https://www.fcc.gov/mobile-deployment-form-477-data (last visited December 22, 2020).

Kenneth Flamm and Anindya Chaudhuri, *An analysis of the determinants of broadband access*, 31 Telecommunications Policy 312 (2007).

Avi Goldfarb & Jeff Prince, *Internet adoption and usage patterns are different: Implications for the digital divide*, 20 Information Economics and Policy 2 (2008).

Government Accounting Office, *Characteristics and Choices of Internet Users*, GAO-01-345 (Feb. 2001), https://www.gao.gov/new.items/d01345.pdf.

Michael Haight et al., *Revisiting the digital divide in Canada: The impact of demographic factors on access to the internet, level of online activity, and social networking site usage,* 17 Information, Communication & Society 503 (2014).

Douglas B. Hindman, *The rural-urban digital divide*, 77 Journalism & Mass Communication Quarterly 549 (2000).

Chatcai Kongaut, & Erik Bohlin, *Impact of broadband speed on economic outputs: An empirical study of OECD countries*, 3 Economics and Business Review 12 (2017).

Karen Mossberger et al., *Broadband adoption: measuring digital citizenship: Mobile access and broadband*, 6 International Journal of Communication, 37 (2012).

National Telecommunications and Information Administration, *Falling through the net: A survey of the "have nots" in rural and urban America* (July 12, 1995), https://www.ntia.doc.gov/ntiahome/fallingthru.html.

National Telecommunications and Information Administration,, *Falling through the net II: New data on the digital divide* (July 28, 1998), https://www.ntia.doc.gov/files/ntia/publications/falling-through-net-ii.pdf.

National Telecommunications and Information Administration,, *Falling Through the Net: Defining the Digital Divide* (July 08, 1999), https://www.ntia.doc.gov/legacy/ntiahome/fttn99/contents.html.

Katy E. Pearce & Ronald E. Rice, *Digital divides from access to activities: Comparing mobile and personal computer Internet users*, 63 Journal of Communication 721 (2013).

James E. Prieger, *The supply side of the digital divide: Is there equal availability in the broadband Internet access market?*, 41 Economic Inquiry, 346 (2003).

James E. Prieger, J. E., & Wei-Min Hu, *The broadband digital divide and the nexus of race, competition, and quality*, 20 Information economics and Policy, 150 (2008).

James E. Prieger, *The broadband digital divide and the economic benefits of mobile broadband for rural areas,* 37 Telecommunications Policy 483 (2013).

Lorna Philip et al., *The digital divide: Patterns, policy and scenarios for connecting the 'final few' in rural communities across Great Britain*, 54 Journal of Rural Studies 386 (2017).

Dean Riddlesden & Alex D. Singleton, *Broadband speed equity: A new digital divide?*, 52 Applied Geography, 25 (2014).

Ibrahaim K. Rohman, & Erik Bohlin, *Does broadband speed really matter for driving economic growth? Investigating OECD countries,* 5 International Journal of Management 2 (2012).

Ibrahaim K. Rohman, & Erik Bohlin, *The impact of broadband speed on the household income: comparing OECD and brics*, Working Paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2226899 (2013).

RootMetrics, *Connected Insights for Your Connected Lifestyle*, http://www.rootmetrics.com/en-US/home (last visited Dec. 9, 2020).

Raimund Schatz, & Sebastian Egger, *Vienna surfing: assessing mobile broadband quality in the field*, Proceedings of the first ACM SIGCOMM workshop on Measurements up the stack 19 (2011).

Speedtest, *Ookla Speedtest Apps for Mobile*, http://www.speedtest.net/mobile/ (last visited Dec. 9, 2020).

Speedtest, *How does Ookla determine ISP names? How can I change this information?*, https://support.ookla.com/hc/en-us/articles/234578348-How-does-Ookla-determine-ISP-names-How-can-I-change-this-information-, (last visited Dec. 9, 2020).

Speedtest, *Speedtest Support*, https://help.speedtest.net/hc/en-us (last visited Dec. 9, 2020).

United States Census, *Glossary*, https://www.census.gov/glossary/#term_Notinlaborforce (last visited Dec. 9, 2020).

Scott Wallsten & Colleen Mallahan. *Residential broadband competition in the United States*, Working Paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1684236 (2010).

Kenneth R. Wilson et al., *Social stratification and the digital divide*, 21 Social Science Computer Review 133 (2003).

Appendix A: Name Cleaning Rules

To assign provider names, we used a combination of the network names and mobile network codes that appear in the Ookla data. We used this combination of names and codes in order to identify sub-brands (such as Cricket to AT&T), or MVNOs, which may operate over the network of one of the nationwide facilities-based providers, but which may apply different data limits and throttling rules. The Ookla Android output includes names and codes as reported by both the device and the Sim Card, while the iOS output only includes names and codes as reported by the device. We did not include tests that were taken when the phone was roaming.

These variables were occasionally corrupt, and occasionally the information did not precisely match between these categories, thus we matched as many of these identifying variables as possible when identifying the provider. Network assignment occurred based on a system of priority – more agreement between different pieces of information and agreement between more reliable information is given higher priority. We prioritized network information reported by the device over information reported by the Sim Card. Specifically, after cleaning the codes and the names, we assigned provider names with the following priorities for the Android operating system and iOS:

- Android:
    - Priority 1: NOC (Network Operator Code) = NON (Network Operator Name) = SOC (Sim Operator Code) = SON (Sim Operator Name);
    - Priority 2: NOC=NON=SOC;
    - Priority 3: NOC=NON=SON;
    - Priority 4: NOC=NON;
    - Priority 5: NON=SOC=SON;
    - Priority 6: NOC=SOC=SON;
    - Priority 7: NON=SON;
    - Priority 8: NOC=SOC
    - Priority 9: NON;
    - Priority 10: not assigned.
- iOS:
    - Priority 1: NOC=NON;
    - Priority 2: NON;
    - Priority 3: not assigned.

Appendix B: Summary Statistics

Table B.1: Number of Samples by Carrier and Technology

Provider \ Technology Generation	3G	4G	LTE	WIFI	Total by Provider
Other	41,561	23,617	285,190	7,584,803	**7,935,171**
AT&T	94,350	79,925	1,652,689	12,458,425	**14,285,389**
AT&T Affiliate	15,063	30,810	242,327	851,350	**1,139,550**
Sprint	46,323	0	924,269	3,450,336	**4,420,928**
Sprint Affiliate	13,665	0	89,256	290,198	**393,119**
T-Mobile	42,783	127,508	2,201,653	4,804,761	**7,176,705**
T-Mobile Affiliate	4,412	38,544	347,179	608,274	**998,409**
Verizon	22,580	0	1,821,095	11,928,313	**13,771,988**
US Cellular	1,457	0	31,494	305,899	**338,850**
Total by Technology	**282,194**	**300,404**	**7,595,152**	**42,282,359**	**50,460,109**

Table B.2: Percentage of Sample by Carrier and Technology

Provider \ Technology Generation	3G	4G	LTE	WIFI	Total by Provider
Other	0.52%	0.30%	3.59%	95.58%	15.73%
AT&T	0.66%	0.56%	11.57%	87.21%	28.31%
AT&T Affiliate	1.32%	2.70%	21.27%	74.71%	2.26%
Sprint	1.05%	0.00%	20.91%	78.05%	8.76%
Sprint Affiliate	3.48%	0.00%	22.70%	73.82%	0.78%
T-Mobile	0.60%	1.78%	30.68%	66.95%	14.22%
T-Mobile Affiliate	0.44%	3.86%	34.77%	60.92%	1.98%
Verizon	0.16%	0.00%	13.22%	86.61%	27.29%
US Cellular	0.43%	0.00%	9.29%	90.28%	0.67%
Entire Sample	0.56%	0.60%	15.05%	83.79%	100.00%

Table B.3: Speed Summary Statistics

	N (millions)	Mean	SD	25th Pct.	Median	75th Pct.	Skewness
3G							
Download	0.3	3.8	9.0	0.7	1.9	4.3	17.5
Upload	0.3	1.1	4.6	0.3	0.8	1.1	47.2
Non-LTE 4G							
Download	0.3	5.0	5.5	1.7	3.8	7.0	8.5
Upload	0.3	1.4	2.1	0.6	1.2	1.7	48.5
LTE							
Download	7.6	21.2	22.6	5.0	13.7	30.2	2.5
Upload	7.6	8.7	9.7	1.8	5.5	12.7	8.0
WiFi							
Download	42.3	42.5	284.8	10.3	26.7	57.1	5,964.2
Upload	42.3	14.6	31.8	2.6	6.2	12.4	9.6

Table B.4: Log Download Speed Correlations

	3G		Non-LTE 4G		LTE		WiFi	
	Ind.	County	Ind.	County	Ind.	County	Ind.	County
Log Providers Count	0.04	0.08	0.11	0.14	0.03	0.06	0.06	0.14
Log Population Density	0.13	0.05	0.10	0.16	0.05	0.13	0.19	0.16
Log Median Household Income ($)	0.10	0.12	0.05	0.09	0.06	0.18	0.14	0.09
Log Median Age (Years)	-0.06	-0.08	-0.01	-0.10	0.04	0.02	-0.08	-0.10
Bachelor's Degree or More (%)	0.11	0.14	0.08	0.13	0.07	0.20	0.15	0.13
Other Race (% of total pop)	0.09	0.10	-0.02	0.02	-0.05	-0.08	0.09	0.02
African American (%)	0.04	-0.01	0.06	0.08	0.01	-0.06	0.05	0.08
African American (%)	-0.04	-0.04	-0.08	-0.12	-0.03	-0.06	-0.06	-0.12
Native American (%)	0.12	0.10	0.04	0.07	0.02	0.09	0.11	0.07
Asian (%)	0.07	0.13	-0.01	0.06	-0.07	-0.09	0.07	0.06
Hispanic (%)	-0.04	-0.07	-0.03	-0.03	-0.03	-0.11	-0.07	-0.03
No telephone Service (%)	0.02	-0.03	0.01	0.01	-0.02	-0.08	0.04	0.01
Unemployed (%)	-0.08	-0.10	-0.07	-0.11	-0.05	-0.17	-0.14	-0.11

Table B.5: Log Upload Speed Correlations

	3G		Non-LTE 4G		LTE		WiFi	
	Ind.	**County**	**Ind.**	**County**	**Ind.**	**County**	**Ind.**	**County**
Log Providers	0.03	0.12	0.09	0.12	0.03	0.07	0.09	0.12
Log Population Density	0.04	0.10	0.10	0.15	0.13	0.16	0.25	0.15
Log Median Household Income ($)	0.03	0.18	0.02	0.14	0.05	0.18	0.18	0.14
Log Median Age (Years)	-0.04	-0.11	-0.07	-0.13	-0.05	-0.15	-0.09	-0.13
Bachelor's Degree or More (%)	0.04	0.19	0.06	0.16	0.09	0.25	0.20	0.16
Other Race (%)	0.02	0.09	0.00	0.08	0.06	0.09	0.11	0.08
African American (%)	0.02	-0.02	0.07	0.02	0.04	-0.05	0.08	0.02
African American (%)	-0.01	-0.05	-0.04	-0.06	-0.03	-0.04	-0.06	-0.06
Native American (%)	0.02	0.10	0.01	0.11	0.08	0.19	0.13	0.11
Asian (%)	0.02	0.10	0.04	0.12	0.03	0.06	0.07	0.12
Hispanic (%)	-0.01	-0.09	0.00	-0.04	-0.01	-0.10	-0.08	-0.04
No telephone Service (%)	0.00	-0.03	0.02	0.00	0.04	-0.06	0.04	0.00
Unemployed (%)	-0.05	-0.20	-0.09	-0.17	-0.08	-0.25	-0.18	-0.17

Appendix C: Results

Table C.1: Logit Observations and Goodness of Fit by Month

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
Observations	7,952,450	7,836,701	8,576,183	8,266,027	7,836,701	9,100,624
Log Likelihood	3,793,680	3,415,804	3,952,839	3,704,576	3,415,804	3,749,257
McFadden's R^2	0.07	0.18	0.08	0.08	0.09	0.08

Table C.2: Logit Demographic Variables

		16-Jul	16-Aug	16-Sep	16-Oct	16-Nov	16-Dec
Population Density (Log)	3G	-0.24***	-0.22***	-0.23***	-0.25***	-0.27***	-0.27***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Non-LTE 4G	-0.19***	-0.17***	-0.18***	-0.17***	-0.18***	-0.19***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	LTE	-0.03***	-0.01	-0.00	-0.02**	-0.03***	-0.03***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bachelors or More (%)	3G	-0.26	-0.41	-0.39	-0.33	-0.28	-0.31
		(0.22)	(0.26)	(0.26)	(0.25)	(0.27)	(0.29)
	Non-LTE 4G	-0.05	-0.19	0.05	-0.06	0.15	0.25
		(0.32)	(0.34)	(0.33)	(0.31)	(0.36)	(0.37)
	LTE	-0.09	-0.36***	-0.32**	-0.31**	-0.22*	-0.23*
		(0.12)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
Other Race (%)	3G	0.55	0.10	0.85**	0.79*	0.22	0.15
		(0.40)	(0.45)	(0.39)	(0.41)	(0.44)	(0.39)
	Non-LTE 4G	0.58	-0.11	0.38	0.65	0.20	-0.20
		(0.46)	(0.50)	(0.55)	(0.46)	(0.48)	(0.56)
	LTE	-0.12	-0.12	0.09	0.41*	0.15	0.10
		(0.17)	(0.16)	(0.19)	(0.25)	(0.18)	(0.20)
Black or African American (%)	3G	0.56***	0.72***	0.46***	0.34*	0.84***	0.83***
		(0.15)	(0.17)	(0.18)	(0.18)	(0.18)	(0.19)
	Non-LTE 4G	1.24***	1.22***	1.29***	1.44***	1.35***	1.26***
		(0.22)	(0.24)	(0.24)	(0.24)	(0.24)	(0.26)
	LTE	0.59***	0.64***	0.46***	0.48***	0.51***	0.45***
		(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)
American Indian and Alaska Native (%)	3G	2.93***	3.15***	2.74***	3.67***	3.54***	3.81***
		(0.44)	(0.50)	(0.51)	(0.51)	(0.48)	(0.45)
	Non-LTE 4G	4.17***	4.39***	3.88***	4.16***	4.03***	4.10***
		(0.49)	(0.63)	(0.57)	(0.54)	(0.54)	(0.57)
	LTE	1.33***	1.05***	0.84***	1.19***	1.12***	1.27***

		(0.26)	(0.27)	(0.24)	(0.23)	(0.23)	(0.32)
Asian (%)	3G	2.30***	2.28***	2.45***	2.71***	3.16***	2.75***
		(0.35)	(0.31)	(0.32)	(0.38)	(0.34)	(0.34)
	Non-LTE 4G	2.52***	1.96***	2.60***	2.74***	2.46***	3.27***
		(0.50)	(0.54)	(0.58)	(0.48)	(0.49)	(0.51)
	LTE	0.51***	0.63***	0.75***	0.86***	1.01***	0.71***
		(0.20)	(0.21)	(0.21)	(0.19)	(0.25)	(0.20)
Hispanic or Latino (%)	3G	0.77***	1.03***	0.70***	0.61***	0.76***	0.84***
		(0.19)	(0.24)	(0.24)	(0.22)	(0.24)	(0.21)
	Non-LTE 4G	1.27***	1.57***	1.29***	0.82***	0.89***	1.29***
		(0.28)	(0.32)	(0.30)	(0.28)	(0.26)	(0.26)
	LTE	0.47***	0.55***	0.46***	0.31***	0.33***	0.35***
		(0.10)	(0.10)	(0.10)	(0.12)	(0.11)	(0.13)
Median Age (Log)	3G	0.39**	0.51***	0.38*	0.19	0.33	0.41*
		(0.18)	(0.19)	(0.20)	(0.20)	(0.22)	(0.25)
	Non-LTE 4G	0.36*	0.55**	0.57**	0.48**	0.64**	0.54**
		(0.22)	(0.22)	(0.25)	(0.22)	(0.25)	(0.25)
	LTE	-0.02	0.09	-0.04	-0.12	-0.10	-0.05
		(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.10)
Mean Travel Time (Log Minutes)	3G	0.39***	0.32***	0.32***	0.44***	0.47***	0.37***
		(0.10)	(0.10)	(0.10)	(0.10)	(0.12)	(0.12)
	Non-LTE 4G	0.07	0.17	0.12	0.04	0.03	-0.07
		(0.13)	(0.13)	(0.14)	(0.13)	(0.14)	(0.16)
	LTE	-0.03	-0.07	-0.12**	-0.04	0.02	-0.02
		(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Mean Household Size (Log)	3G	-1.57***	-1.75***	-1.69***	-1.74***	-1.82***	-1.62***
		(0.42)	(0.49)	(0.53)	(0.48)	(0.53)	(0.46)
	Non-LTE 4G	-2.19***	-2.35***	-2.14***	-1.59***	-1.36***	-1.34***
		(0.60)	(0.68)	(0.68)	(0.54)	(0.50)	(0.51)
	LTE	-0.98***	-1.01***	-1.00***	-0.96***	-0.94***	-0.77***
		(0.18)	(0.19)	(0.21)	(0.23)	(0.23)	(0.28)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.3: Logit Economic Variables

		Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
Median Household Income (Log $)	3G	-0.39***	-0.23	-0.32**	-0.45***	-0.42**	-0.49***
		(0.13)	(0.16)	(0.16)	(0.15)	(0.17)	(0.15)
	Non-LTE 4G	-0.02	0.15	-0.04	-0.23	-0.24	-0.34
		(0.21)	(0.23)	(0.22)	(0.19)	(0.20)	(0.21)
	LTE	-0.13**	0.02	0.01	-0.04	-0.10	-0.19**
		(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)
Unemployed (%)	3G	-4.12***	-3.59**	-4.74***	-5.88***	-5.09***	-6.70***
		(1.48)	(1.67)	(1.61)	(1.76)	(1.73)	(1.76)
	Non-LTE 4G	-0.13	-0.88	-2.17	-3.75	-1.92	-1.33
		(2.09)	(2.50)	(2.33)	(2.36)	(2.31)	(2.41)
	LTE	-1.20*	-0.44	0.45	-0.37	-0.20	-0.79
		(0.72)	(0.76)	(0.75)	(0.78)	(0.79)	(0.80)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.4: Logit Technological Variables

		Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
iOS	3G	-0.38***	-0.62***	-0.38***	-0.38***	-0.39***	-0.34***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
	LTE	-0.56***	-0.76***	-0.55***	-0.53***	-0.57***	-0.52***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Minimum Effective Radius	3G	0.11*	0.06	0.07	0.07	0.03	0.05
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
	Non-LTE 4G	0.04	0.12	0.10	0.02	0.12	0.16
		(0.09)	(0.09)	(0.11)	(0.10)	(0.08)	(0.11)
	LTE	-0.05	-0.05	-0.03	-0.00	-0.00	0.03
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
No telephone service	3G	1.15	2.26*	3.99***	1.52	2.53**	2.96**
		(1.23)	(1.22)	(1.03)	(1.17)	(1.27)	(1.19)
	Non-LTE 4G	3.95**	6.48***	3.29**	2.51	0.35	2.06
		(1.59)	(1.65)	(1.63)	(1.57)	(1.66)	(1.81)
	LTE	0.45	0.82*	0.73	0.89	1.30**	1.31**
		(0.50)	(0.49)	(0.51)	(0.56)	(0.52)	(0.59)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.5: Logit Area-Weighted Log Provider

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
Log(1+Own Tech Provider Counts)	0.25***	0.20***	0.22***	0.21***	0.23***	0.17***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Log(1+WiFi Provider Counts)						
3G	0.07	0.19	-0.01	0.12	0.21	0.18
	(0.13)	(0.14)	(0.14)	(0.15)	(0.14)	(0.13)
Non-LTE 4G	0.41**	0.33	0.06	0.24	0.24	0.17
	(0.19)	(0.21)	(0.19)	(0.19)	(0.20)	(0.21)
LTE	-0.02	0.05	0.02	0.05	0.01	0.05
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.6: Logit 3G Hours Fixed Effects

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
1:00 AM	0.07*	0.19***	0.07	0.07	0.02	0.21***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
2:00 AM	0.24***	0.24***	0.18***	0.15***	0.13**	0.19***
	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
3:00 AM	0.18***	0.16***	0.28***	0.20***	0.22***	0.31***
	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
4:00 AM	0.04	0.11*	0.08	0.10	0.10	0.18***
	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)
5:00 AM	0.08	0.14**	0.05	0.07	0.07	0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
6:00 AM	0.14***	0.08	0.11*	-0.05	0.12**	0.07
	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)
7:00 AM	0.09**	0.19***	0.18***	0.06	0.15***	0.16***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
8:00 AM	0.24***	0.29***	0.26***	0.20***	0.22***	0.24***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
9:00 AM	0.27***	0.36***	0.29***	0.27***	0.26***	0.30***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
10:00 AM	0.34***	0.37***	0.34***	0.29***	0.33***	0.38***
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)
11:00 AM	0.37***	0.44***	0.38***	0.36***	0.32***	0.46***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
12:00 PM	0.42***	0.48***	0.42***	0.34***	0.41***	0.48***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
1:00 PM	0.42***	0.47***	0.43***	0.37***	0.39***	0.48***

	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
2:00 PM	0.39***	0.44***	0.42***	0.34***	0.39***	0.47***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
3:00 PM	0.33***	0.35***	0.38***	0.29***	0.34***	0.43***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
4:00 PM	0.27***	0.28***	0.28***	0.20***	0.23***	0.32***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
5:00 PM	0.21***	0.21***	0.23***	0.18***	0.18***	0.26***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
6:00 PM	0.17***	0.18***	0.18***	0.14***	0.07*	0.20***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
7:00 PM	0.16***	0.13***	0.07*	0.03	-0.01	0.16***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
8:00 PM	0.01	0.02	-0.02	-0.11***	-0.13***	0.02
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
9:00 PM	-0.02	-0.09**	-0.16***	-0.18***	-0.16***	-0.02
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
10:00 PM	-0.10***	-0.11***	-0.13***	-0.18***	-0.19***	-0.07
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
11:00 PM	-0.07**	-0.08**	-0.07*	-0.16***	-0.13***	-0.02
	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.7: Logit Non-LTE 4G Hours Fixed Effects

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
1:00 AM	0.10***	0.07*	0.19***	0.11**	0.15***	0.09**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
2:00 AM	0.28***	0.23***	0.33***	0.21***	0.25***	0.14***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
3:00 AM	0.24***	0.20***	0.40***	0.24***	0.30***	0.18***
	(0.06)	(0.05)	(0.07)	(0.06)	(0.06)	(0.06)
4:00 AM	0.25***	0.36***	0.36***	0.18***	0.25***	0.25***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
5:00 AM	0.25***	0.17***	0.22***	0.12*	0.21***	0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
6:00 AM	0.09**	0.06	0.13***	0.07	0.11*	0.06
	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)
7:00 AM	0.07	0.16***	0.24***	0.17***	0.09*	0.04
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
8:00 AM	0.15***	0.18***	0.22***	0.12***	0.13***	0.09**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
9:00 AM	0.12***	0.15***	0.17***	0.05	0.15***	0.12***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
10:00 AM	0.20***	0.17***	0.29***	0.16***	0.20***	0.12***
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
11:00 AM	0.24***	0.26***	0.34***	0.22***	0.25***	0.24***
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
12:00 PM	0.32***	0.31***	0.39***	0.29***	0.32***	0.27***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
1:00 PM	0.30***	0.28***	0.37***	0.28***	0.28***	0.27***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
2:00 PM	0.28***	0.24***	0.30***	0.23***	0.30***	0.27***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
3:00 PM	0.22***	0.22***	0.30***	0.19***	0.26***	0.25***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
4:00 PM	0.18***	0.16***	0.26***	0.19***	0.19***	0.18***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
5:00 PM	0.13***	0.13***	0.20***	0.09**	0.14***	0.11***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
6:00 PM	0.10***	0.08**	0.15***	0.04	0.07	0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
7:00 PM	0.06**	0.02	0.06*	-0.06*	-0.02	-0.03
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
8:00 PM	-0.04	-0.05	-0.05	-0.09**	-0.13***	-0.11***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)

9:00 PM	-0.09***	-0.17***	-0.12***	-0.17***	-0.15***	-0.11***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
10:00 PM	-0.15***	-0.14***	-0.14***	-0.17***	-0.15***	-0.16***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
11:00 PM	-0.11***	-0.09***	-0.06*	-0.12***	-0.09**	-0.15***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.8: Logit LTE Hours Fixed Effects

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
1:00 AM	0.12***	0.13***	0.10***	0.10***	0.11***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2:00 AM	0.21***	0.22***	0.20***	0.17***	0.21***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
3:00 AM	0.28***	0.27***	0.26***	0.20***	0.27***	0.27***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
4:00 AM	0.28***	0.26***	0.25***	0.18***	0.21***	0.23***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
5:00 AM	0.23***	0.19***	0.15***	0.10***	0.14***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
6:00 AM	0.17***	0.13***	0.12***	0.08***	0.09***	0.08***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
7:00 AM	0.20***	0.21***	0.20***	0.19***	0.18***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
8:00 AM	0.22***	0.23***	0.22***	0.19***	0.19***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
9:00 AM	0.22***	0.23***	0.21***	0.18***	0.19***	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
10:00 AM	0.24***	0.25***	0.24***	0.21***	0.23***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
11:00 AM	0.31***	0.33***	0.30***	0.28***	0.29***	0.25***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
12:00 PM	0.39***	0.40***	0.38***	0.36***	0.38***	0.34***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1:00 PM	0.38***	0.40***	0.36***	0.35***	0.37***	0.33***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2:00 PM	0.34***	0.36***	0.34***	0.32***	0.34***	0.32***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
3:00 PM	0.29***	0.30***	0.28***	0.27***	0.30***	0.27***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
4:00 PM	0.25***	0.23***	0.20***	0.21***	0.23***	0.20***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
5:00 PM	0.20***	0.18***	0.16***	0.17***	0.17***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
6:00 PM	0.17***	0.13***	0.11***	0.11***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
7:00 PM	0.14***	0.08***	0.05***	0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
8:00 PM	0.06***	-0.03**	-0.09***	-0.10***	-0.11***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

9:00 PM	-0.04***	-0.13***	-0.17***	-0.17***	-0.16***	-0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
10:00 PM	-0.10***	-0.14***	-0.17***	-0.17***	-0.15***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
11:00 PM	-0.07***	-0.10***	-0.11***	-0.11***	-0.09***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.9: Logit Carrier Fixed Effects

		16-Jul	16-Aug	16-Sep	16-Oct	16-Nov	16-Dec
AT&T	3G	0.27***	0.45***	0.54***	0.57***	0.57***	0.65***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Non-LTE 4G	1.40***	1.27***	1.33***	1.44***	1.48***	1.42***
		(0.10)	(0.12)	(0.08)	(0.07)	(0.07)	(0.06)
	LTE	1.30***	1.43***	1.42***	1.35***	1.26***	1.39***
		(0.02)	(0.03)	(0.02)	(0.03)	(0.09)	(0.02)
AT&T Affiliate	3G	0.84***	1.06***	1.10***	1.21***	1.19***	1.30***
		(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
	Non-LTE 4G	1.96***	1.88***	1.96***	2.02***	2.11***	2.04***
		(0.10)	(0.12)	(0.09)	(0.07)	(0.07)	(0.07)
	LTE	1.77***	1.83***	1.87***	1.85***	1.81***	1.93***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.10)	(0.03)
Sprint	3G	1.00***	1.18***	1.08***	0.95***	0.99***	0.97***
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
	LTE	1.80***	1.96***	2.00***	1.96***	1.88***	1.99***
		(0.02)	(0.02)	(0.02)	(0.03)	(0.09)	(0.02)
Sprint Affiliate	3G	1.92***	2.05***	2.10***	2.16***	2.13***	2.17***
		(0.05)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)
	LTE	1.70***	1.80***	1.93***	1.94***	1.90***	2.08***
		(0.03)	(0.04)	(0.04)	(0.04)	(0.09)	(0.03)
T-Mobile	3G	0.49***	0.62***	0.80***	0.73***	0.71***	0.62***
		(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	Non-LTE 4G	2.05***	1.96***	2.12***	2.27***	2.33***	2.14***
		(0.11)	(0.13)	(0.10)	(0.08)	(0.07)	(0.06)
	LTE	2.27***	2.39***	2.54***	2.54***	2.47***	2.53***
		(0.02)	(0.02)	(0.03)	(0.03)	(0.10)	(0.02)
T-Mobile Affiliate	3G	0.21***	0.35***	0.48***	0.35***	0.27**	0.21**
		(0.07)	(0.09)	(0.11)	(0.10)	(0.11)	(0.09)
	Non-LTE 4G	2.49***	2.33***	2.38***	2.53***	2.60***	2.51***
		(0.11)	(0.14)	(0.09)	(0.08)	(0.08)	(0.07)
	LTE	2.45***	2.50***	2.54***	2.49***	2.40***	2.52***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.10)	(0.03)
Verizon	3G	-1.16***	-0.99***	-1.06***	-0.99***	-1.02***	-1.06***
		(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
	Non-LTE 4G	1.25***	1.50***	1.58***	1.45***	1.31***	1.41***
		(0.02)	(0.02)	(0.02)	(0.03)	(0.09)	(0.02)
US Cellular	3G	-0.71***	-0.35***	-0.39***	-0.61***	-0.50***	-0.52***
		(0.10)	(0.09)	(0.09)	(0.11)	(0.11)	(0.10)
	Non-LTE 4G	0.76***	0.90***	0.98***	0.91***	0.82***	0.92***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.09)	(0.03)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.10: Logit 3G State Fixed Effects

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
AK	0.94***	0.80***	0.61***	0.52**	0.75***	0.75***
	(0.21)	(0.22)	(0.19)	(0.21)	(0.22)	(0.24)
AZ	-0.46***	-0.41***	-0.59***	-0.62***	-0.30**	-0.07
	(0.13)	(0.15)	(0.15)	(0.16)	(0.12)	(0.14)
AR	-0.05	-0.19*	-0.38***	-0.23*	0.14	-0.15
	(0.12)	(0.11)	(0.12)	(0.14)	(0.10)	(0.14)
CA	0.26**	0.24*	0.18	0.15	0.40***	0.47***
	(0.13)	(0.13)	(0.12)	(0.14)	(0.13)	(0.14)
CO	-0.02	-0.06	-0.28**	-0.37**	-0.09	-0.07
	(0.12)	(0.14)	(0.14)	(0.15)	(0.13)	(0.14)
CT	0.31***	0.29**	0.13	0.09	0.32***	0.37***
	(0.12)	(0.13)	(0.14)	(0.15)	(0.11)	(0.12)
DE	0.41***	0.26	0.15	0.23	0.27***	0.29***
	(0.09)	(0.18)	(0.22)	(0.15)	(0.10)	(0.10)
DC	1.12***	0.92***	0.96***	1.01***	0.99***	0.74***
	(0.13)	(0.16)	(0.16)	(0.16)	(0.16)	(0.15)
FL	-0.47***	-0.53***	-0.55***	-0.44***	-0.14	-0.15
	(0.10)	(0.12)	(0.10)	(0.12)	(0.10)	(0.11)
GA	0.06	0.09	0.01	0.06	0.11	0.13
	(0.09)	(0.10)	(0.10)	(0.12)	(0.08)	(0.11)
HI	0.09	0.03	-0.16	-0.18	0.05	0.28
	(0.20)	(0.24)	(0.20)	(0.22)	(0.21)	(0.21)
ID	0.39**	0.31*	0.20	0.13	0.36***	0.24
	(0.16)	(0.18)	(0.16)	(0.17)	(0.13)	(0.18)
IL	-0.17*	-0.19	-0.29**	-0.37***	-0.16	-0.15
	(0.10)	(0.12)	(0.12)	(0.12)	(0.10)	(0.12)
IN	-0.17*	-0.12	-0.24**	-0.21	-0.12	-0.09
	(0.10)	(0.11)	(0.10)	(0.14)	(0.09)	(0.12)
IA	0.29**	0.03	-0.05	-0.00	0.23*	0.01
	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.14)
KS	-0.04	-0.21	-0.21	-0.12	0.05	0.11
	(0.13)	(0.13)	(0.13)	(0.17)	(0.13)	(0.15)
KY	-0.11	-0.07	-0.26**	-0.44***	-0.12	-0.38***
	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)
LA	0.08	0.19	0.05	-0.08	-0.02	0.07

	(0.12)	(0.12)	(0.13)	(0.14)	(0.12)	(0.12)
ME	0.25***	0.17	0.25	-0.19	0.06	0.10
	(0.10)	(0.16)	(0.15)	(0.15)	(0.13)	(0.17)
MD	0.51***	0.34***	0.23**	0.31**	0.29**	0.30**
	(0.11)	(0.11)	(0.11)	(0.13)	(0.12)	(0.12)
MA	0.43***	0.30**	0.31**	0.18	0.44***	0.43***
	(0.13)	(0.13)	(0.13)	(0.14)	(0.13)	(0.16)
MI	0.24**	0.30***	0.06	-0.03	0.09	0.01
	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)	(0.12)
MN	0.06	-0.00	-0.29**	-0.33**	-0.24**	-0.31**
	(0.11)	(0.12)	(0.11)	(0.15)	(0.12)	(0.13)
MS	0.02	0.19	-0.08	-0.19	0.01	0.08
	(0.14)	(0.12)	(0.11)	(0.14)	(0.11)	(0.12)
MO	-0.19	-0.13	-0.42***	-0.43***	-0.36***	-0.35***
	(0.12)	(0.13)	(0.11)	(0.13)	(0.09)	(0.12)
MT	0.65***	0.63**	0.30	-0.06	0.23	0.09
	(0.18)	(0.30)	(0.20)	(0.20)	(0.21)	(0.20)
NE	0.01	0.06	-0.01	0.14	-0.00	0.06
	(0.13)	(0.18)	(0.22)	(0.18)	(0.23)	(0.21)
NV	0.11	0.14	-0.03	-0.20	0.11	0.02
	(0.14)	(0.16)	(0.14)	(0.16)	(0.17)	(0.16)
NH	0.24	0.16	-0.09	-0.01	-0.13	0.22
	(0.15)	(0.15)	(0.14)	(0.13)	(0.14)	(0.15)
NJ	0.50***	0.39***	0.39***	0.20	0.46***	0.49***
	(0.12)	(0.12)	(0.11)	(0.14)	(0.11)	(0.13)
NM	-0.34**	-0.47***	-0.44**	-0.37**	-0.39**	-0.31*
	(0.16)	(0.18)	(0.17)	(0.18)	(0.19)	(0.19)
NY	0.60***	0.58***	0.49***	0.50***	0.69***	0.72***
	(0.10)	(0.11)	(0.09)	(0.11)	(0.10)	(0.12)
NC	0.07	0.04	-0.02	0.05	0.12	0.10
	(0.10)	(0.10)	(0.09)	(0.11)	(0.10)	(0.10)
ND	-0.28	-0.37*	-0.45**	-1.06***	-0.27	-0.53*
	(0.18)	(0.19)	(0.19)	(0.22)	(0.29)	(0.29)
OH	-0.03	-0.09	-0.25**	-0.32**	-0.19*	-0.17
	(0.10)	(0.10)	(0.11)	(0.13)	(0.10)	(0.12)
OK	-0.45***	-0.55***	-0.59***	-0.70***	-0.32**	-0.47***
	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)
OR	-0.15	-0.23*	-0.34**	-0.58***	-0.26*	-0.27*

	(0.14)	(0.13)	(0.15)	(0.16)	(0.14)	(0.14)
PA	0.39***	0.32***	0.22**	0.06	0.30***	0.26**
	(0.10)	(0.11)	(0.11)	(0.14)	(0.11)	(0.11)
RI	0.45**	0.16	0.09	0.14	0.57**	0.64***
	(0.22)	(0.26)	(0.13)	(0.27)	(0.24)	(0.23)
SC	0.15	0.04	0.19	0.00	0.18**	0.03
	(0.10)	(0.12)	(0.16)	(0.11)	(0.09)	(0.12)
SD	0.47***	0.32*	0.18	-0.18	0.38*	-0.03
	(0.17)	(0.17)	(0.20)	(0.22)	(0.22)	(0.25)
TN	-0.05	-0.08	-0.25**	-0.27**	-0.04	-0.06
	(0.09)	(0.10)	(0.11)	(0.11)	(0.12)	(0.13)
TX	-0.29***	-0.28**	-0.35***	-0.44***	-0.13	-0.19*
	(0.10)	(0.12)	(0.11)	(0.12)	(0.10)	(0.11)
UT	0.52***	0.52***	0.40***	0.34**	0.49***	0.32**
	(0.12)	(0.13)	(0.12)	(0.15)	(0.13)	(0.15)
VT	0.54***	0.45***	0.15	-0.07	0.09	0.39***
	(0.13)	(0.17)	(0.14)	(0.15)	(0.16)	(0.14)
VA	0.44***	0.49***	0.43***	0.34***	0.54***	0.53***
	(0.10)	(0.11)	(0.10)	(0.11)	(0.09)	(0.11)
WA	-0.02	-0.02	-0.30**	-0.32**	-0.07	-0.10
	(0.12)	(0.13)	(0.12)	(0.13)	(0.14)	(0.13)
WV	0.14	0.25*	0.28**	0.15	0.23*	0.34**
	(0.12)	(0.13)	(0.12)	(0.14)	(0.13)	(0.14)
WI	0.19*	0.01	0.06	-0.08	0.04	0.04
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)
WY	0.80***	0.98***	0.81***	0.50*	0.64**	0.51
	(0.22)	(0.24)	(0.24)	(0.29)	(0.28)	(0.31)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.11: Logit Non-LTE 4G State Fixed Effects

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
AK	1.02***	1.00***	0.91***	1.09***	0.99***	1.00***
	(0.27)	(0.32)	(0.31)	(0.25)	(0.27)	(0.30)
AZ	-0.05	0.03	0.16	0.37**	0.58***	0.64***
	(0.18)	(0.20)	(0.18)	(0.17)	(0.18)	(0.19)
AR	0.01	-0.25*	-0.09	0.11	0.15	0.29
	(0.14)	(0.14)	(0.13)	(0.14)	(0.16)	(0.18)
CA	0.11	0.18	0.22	0.38**	0.40**	0.42**
	(0.18)	(0.18)	(0.18)	(0.17)	(0.17)	(0.19)
CO	0.14	-0.02	0.01	0.19	0.10	0.24
	(0.16)	(0.18)	(0.17)	(0.18)	(0.17)	(0.18)
CT	-0.01	-0.02	0.21	0.16	0.21	0.24
	(0.16)	(0.21)	(0.24)	(0.19)	(0.17)	(0.16)
DE	0.40***	-0.01	-0.17	0.09	0.20	0.31
	(0.15)	(0.24)	(0.12)	(0.13)	(0.17)	(0.25)
DC	0.57***	0.46*	0.73***	0.62***	0.53***	1.12***
	(0.20)	(0.24)	(0.21)	(0.19)	(0.18)	(0.17)
FL	-0.21*	-0.34**	-0.18	0.15	0.08	0.14
	(0.12)	(0.14)	(0.12)	(0.14)	(0.14)	(0.13)
GA	-0.32***	-0.37***	-0.33***	-0.13	-0.13	-0.05
	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)	(0.13)
HI	0.31	0.42	0.13	0.19	0.39	0.56*
	(0.27)	(0.28)	(0.29)	(0.28)	(0.27)	(0.30)
ID	0.46***	0.44***	0.64***	0.76***	0.73***	0.82***
	(0.16)	(0.16)	(0.20)	(0.18)	(0.24)	(0.26)
IL	0.13	0.06	0.16	0.26	0.25	0.29*
	(0.15)	(0.18)	(0.15)	(0.16)	(0.16)	(0.15)
IN	0.14	-0.07	0.06	0.05	0.12	0.25*
	(0.14)	(0.15)	(0.13)	(0.14)	(0.14)	(0.14)
IA	1.08***	0.62***	1.02***	1.01***	1.11***	1.18***
	(0.21)	(0.20)	(0.19)	(0.20)	(0.21)	(0.19)
KS	-0.03	-0.11	0.08	0.17	0.22	0.31
	(0.19)	(0.23)	(0.19)	(0.18)	(0.20)	(0.22)
KY	-0.08	-0.21	0.04	-0.03	0.06	0.12
	(0.14)	(0.15)	(0.17)	(0.15)	(0.14)	(0.15)
LA	-0.55***	-0.64***	-0.49***	-0.44**	-0.06	-0.22

	(0.16)	(0.20)	(0.17)	(0.19)	(0.32)	(0.32)
ME	0.26	-0.06	-0.02	0.06	0.18	-0.23
	(0.18)	(0.19)	(0.21)	(0.18)	(0.17)	(0.20)
MD	0.39**	0.09	0.25*	0.32**	0.29**	0.43***
	(0.17)	(0.15)	(0.15)	(0.16)	(0.15)	(0.15)
MA	0.47***	0.28*	0.18	0.42**	0.46**	0.63***
	(0.16)	(0.17)	(0.15)	(0.16)	(0.20)	(0.19)
MI	0.28**	0.14	0.26**	0.34**	0.14	0.27**
	(0.13)	(0.15)	(0.12)	(0.14)	(0.14)	(0.13)
MN	-0.05	-0.16	0.06	0.02	-0.08	0.08
	(0.14)	(0.16)	(0.14)	(0.14)	(0.14)	(0.15)
MS	-0.23	-0.37**	-0.17	-0.46***	-0.21	-0.12
	(0.17)	(0.16)	(0.17)	(0.17)	(0.14)	(0.15)
MO	-0.19	-0.20	-0.08	0.10	-0.06	-0.12
	(0.14)	(0.14)	(0.14)	(0.20)	(0.17)	(0.14)
MT	0.60***	0.44*	0.49**	0.54**	0.79***	0.98***
	(0.21)	(0.22)	(0.23)	(0.24)	(0.20)	(0.27)
NE	1.62***	1.56***	1.48***	1.71***	1.80***	1.59***
	(0.43)	(0.38)	(0.32)	(0.36)	(0.38)	(0.31)
NV	0.24	0.22	0.28	0.52***	0.51***	0.51**
	(0.17)	(0.19)	(0.20)	(0.19)	(0.18)	(0.21)
NH	-0.24	-0.22	-0.18	0.07	0.09	0.10
	(0.19)	(0.19)	(0.19)	(0.21)	(0.20)	(0.31)
NJ	0.27*	0.28	0.32**	0.43***	0.46***	0.49***
	(0.16)	(0.18)	(0.14)	(0.15)	(0.16)	(0.16)
NM	-0.41*	-0.59**	-0.41	-0.05	-0.35	-0.35
	(0.23)	(0.25)	(0.26)	(0.20)	(0.23)	(0.24)
NY	0.50***	0.37**	0.44***	0.47***	0.43***	0.65***
	(0.13)	(0.15)	(0.13)	(0.14)	(0.15)	(0.17)
NC	-1.15***	-1.24***	-1.08***	-0.81***	-0.89***	-0.83***
	(0.15)	(0.15)	(0.14)	(0.18)	(0.23)	(0.21)
ND	0.35	-0.12	0.04	0.68	0.59*	0.40
	(0.21)	(0.24)	(0.24)	(0.51)	(0.36)	(0.33)
OH	0.10	-0.04	0.04	0.21	0.15	0.41**
	(0.13)	(0.16)	(0.12)	(0.14)	(0.16)	(0.16)
OK	-0.35**	-0.47***	-0.25	0.01	0.17	0.12
	(0.17)	(0.18)	(0.16)	(0.19)	(0.19)	(0.20)
OR	0.03	0.09	0.14	0.20	0.28	0.33*

	(0.17)	(0.18)	(0.17)	(0.19)	(0.18)	(0.20)
PA	0.57***	0.45***	0.51***	0.47***	0.53***	0.70***
	(0.18)	(0.17)	(0.14)	(0.15)	(0.16)	(0.15)
RI	0.13	-0.04	-0.17	0.26	0.33	-0.10
	(0.24)	(0.24)	(0.16)	(0.18)	(0.20)	(0.15)
SC	-0.13	-0.28	-0.20	0.09	0.13	0.11
	(0.16)	(0.18)	(0.19)	(0.18)	(0.21)	(0.17)
SD	0.43*	0.27	0.15	0.56	0.49	0.18
	(0.22)	(0.20)	(0.35)	(0.45)	(0.30)	(0.23)
TN	-0.08	-0.15	-0.11	0.05	0.15	0.17
	(0.13)	(0.15)	(0.15)	(0.13)	(0.13)	(0.14)
TX	-0.35**	-0.45***	-0.27**	-0.13	-0.13	-0.11
	(0.14)	(0.15)	(0.13)	(0.14)	(0.14)	(0.15)
UT	0.58***	0.74***	0.60***	0.77***	0.66***	0.83***
	(0.16)	(0.16)	(0.16)	(0.17)	(0.18)	(0.18)
VT	0.49**	0.25	0.34	0.67***	0.16	0.05
	(0.19)	(0.21)	(0.36)	(0.23)	(0.21)	(0.23)
VA	0.24*	0.06	0.13	0.24	0.12	0.44***
	(0.14)	(0.17)	(0.14)	(0.15)	(0.14)	(0.15)
WA	0.16	0.25	0.28	0.52***	0.62***	0.64***
	(0.17)	(0.18)	(0.19)	(0.18)	(0.19)	(0.20)
WV	0.54***	-0.57**	0.01	-0.02	-0.24	0.07
	(0.17)	(0.22)	(0.22)	(0.24)	(0.24)	(0.21)
WI	0.19	-0.02	0.23	0.38**	0.37**	0.47***
	(0.17)	(0.19)	(0.18)	(0.17)	(0.17)	(0.16)
WY	1.74***	1.95***	2.13***	1.97***	1.92***	2.29***
	(0.36)	(0.34)	(0.29)	(0.32)	(0.38)	(0.40)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.12: Logit LTE State Fixed Effects

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
AK	0.54***	0.55***	0.32***	0.31***	0.45***	0.54***
	(0.11)	(0.10)	(0.08)	(0.09)	(0.11)	(0.11)
AZ	-0.21***	-0.21***	-0.24***	-0.20***	-0.17***	-0.09
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)
AR	0.05	0.08	0.07	0.03	0.12**	0.17***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)
CA	0.07	0.01	-0.08	-0.06	-0.01	0.10
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
CO	-0.13**	-0.15**	-0.22***	-0.19***	-0.19***	-0.17**
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
CT	-0.06	-0.11*	-0.22***	-0.22***	-0.17***	-0.10
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
DE	0.06	0.06	-0.12*	-0.16**	-0.10	0.01
	(0.05)	(0.06)	(0.06)	(0.08)	(0.06)	(0.05)
DC	0.19***	0.01	0.05	0.05	0.11*	0.31***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)
FL	-0.18***	-0.22***	-0.23***	-0.16***	-0.11**	-0.08
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
GA	0.07	-0.01	-0.06	0.01	-0.00	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
HI	0.16	0.09	-0.00	-0.11	-0.05	0.20*
	(0.10)	(0.10)	(0.11)	(0.10)	(0.12)	(0.11)
ID	0.23***	0.20***	0.13**	0.13**	0.21***	0.18**
	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)
IL	0.03	-0.08	-0.12**	-0.14***	-0.11**	-0.05
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
IN	-0.03	-0.11**	-0.15***	-0.13***	-0.09*	-0.07
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
IA	0.05	-0.03	-0.11*	-0.12**	-0.14***	-0.07
	(0.06)	(0.08)	(0.06)	(0.05)	(0.05)	(0.06)
KS	0.08	0.05	0.04	0.04	0.02	0.03
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
KY	-0.09	-0.08	-0.09	-0.08	-0.07	-0.04
	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)

LA	0.02	0.00	0.00	0.01	-0.02	0.01
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
ME	-0.08	-0.08	-0.19***	-0.28***	-0.30***	-0.20***
	(0.06)	(0.06)	(0.07)	(0.08)	(0.07)	(0.07)
MD	0.12**	0.05	0.03	-0.02	0.06	0.13**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
MA	0.08	0.02	-0.11***	-0.13**	-0.07	0.02
	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)
MI	0.06	-0.01	-0.07*	-0.08**	-0.07*	-0.03
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
MN	0.07	0.06	-0.08*	-0.09**	-0.06	0.01
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)
MS	0.21***	0.24***	0.31***	0.22***	0.21***	0.35***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
MO	-0.01	-0.03	-0.08*	-0.10*	-0.07	-0.07
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
MT	0.00	0.00	-0.07	-0.26***	-0.16**	-0.15
	(0.08)	(0.08)	(0.06)	(0.07)	(0.07)	(0.09)
NE	-0.05	-0.05	-0.20***	-0.17**	-0.18***	-0.15**
	(0.07)	(0.07)	(0.06)	(0.08)	(0.07)	(0.06)
NV	-0.00	-0.03	-0.08	-0.03	-0.00	0.12*
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
NH	-0.02	-0.21***	-0.26***	-0.39***	-0.31***	-0.20***
	(0.07)	(0.06)	(0.07)	(0.08)	(0.09)	(0.08)
NJ	0.17***	0.08	-0.01	-0.04	0.00	0.08
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)
NM	-0.23***	-0.19***	-0.15**	-0.14*	-0.13*	-0.10
	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.09)
NY	0.13**	0.07	-0.03	-0.01	0.05	0.10**
	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)
NC	-0.27***	-0.35***	-0.39***	-0.30***	-0.31***	-0.25***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
ND	-0.04	-0.00	-0.15*	-0.32***	-0.16**	-0.19**
	(0.08)	(0.10)	(0.08)	(0.07)	(0.07)	(0.09)
OH	0.02	-0.03	-0.08*	-0.06	-0.05	-0.00
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
OK	0.02	0.01	0.00	-0.05	-0.01	-0.00

	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
OR	0.03	-0.06	-0.13**	-0.16***	-0.09	-0.05
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)
PA	0.12*	0.08	0.03	-0.06	-0.05	0.04
	(0.07)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)
RI	0.01	-0.09	-0.15**	-0.17***	-0.02	0.09
	(0.07)	(0.08)	(0.06)	(0.06)	(0.09)	(0.07)
SC	-0.01	-0.02	-0.11**	-0.00	-0.02	0.04
	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
SD	-0.01	0.03	-0.04	-0.16*	0.01	-0.17*
	(0.09)	(0.09)	(0.08)	(0.09)	(0.14)	(0.10)
TN	0.04	0.02	-0.04	-0.03	-0.01	0.04
	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
TX	-0.04	-0.09*	-0.13***	-0.10**	-0.06	-0.05
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
UT	0.07	0.09	-0.00	-0.02	0.06	0.06
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
VT	-0.39***	-0.43***	-0.58***	-0.63***	-0.51***	-0.42***
	(0.11)	(0.08)	(0.07)	(0.08)	(0.10)	(0.08)
VA	0.22***	0.13***	0.12***	0.09**	0.13***	0.22***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
WA	0.11	0.09	-0.02	-0.04	0.15	0.04
	(0.07)	(0.08)	(0.08)	(0.07)	(0.12)	(0.07)
WV	0.10	0.03	-0.00	-0.05	-0.03	-0.05
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)
WI	0.15**	-0.00	-0.09*	-0.11**	-0.05	-0.03
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
WY	0.11	-0.03	-0.06	-0.17*	-0.08	-0.00
	(0.09)	(0.11)	(0.09)	(0.09)	(0.09)	(0.11)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.13: Logit Technology Specific Constants

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16
3G	-1.21	-3.42**	-1.63	0.08	-1.21	-0.60
	(1.17)	(1.39)	(1.32)	(1.21)	(1.44)	(1.29)
Non-LTE 4G	-4.77***	-7.39***	-5.15***	-3.35**	-4.28**	-2.72
	(1.73)	(1.83)	(1.79)	(1.65)	(1.83)	(1.93)
LTE	-0.66	-2.81***	-2.08***	-1.47**	-1.03*	-0.47
	(0.57)	(0.62)	(0.59)	(0.59)	(0.61)	(0.63)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.14: OLS Observations and Goodness of Fit

Dependent Variable	Independent Variable	Subsample 3G	Non-LTE 4G	LTE	WiFi
Observations		282,194	300,404	7,595,152	42,282,359
R-squared	Download	0.23	0.06	0.08	0.06
	Upload	0.02	0.06	0.06	0.10

Table C.15: OLS Demographic Variables

Dependent Variable	Independent Variable (Log(1+KBps))	Subsample 3G	4G Non-LTE	LTE	WiFi
Population Density (Log)	Download	0.06***	0.05***	0.05***	0.19***
		(0.01)	(0.01)	(0.01)	(0.01)
	Upload	0.04***	0.07***	0.13***	0.18***
		(0.01)	(0.01)	(0.01)	(0.02)
Bachelors or More (%)	Download	-0.04	-0.13	0.55***	-0.21
		(0.14)	(0.22)	(0.14)	(0.16)
	Upload	-0.13	-0.19	0.10	0.69***
		(0.10)	(0.13)	(0.13)	(0.25)
Other Race (%)	Download	0.20	-1.05*	-0.50	0.56**
		(0.24)	(0.54)	(0.42)	(0.27)
	Upload	0.27	-0.68**	-0.35	1.91***
		(0.18)	(0.27)	(0.33)	(0.36)
Black or African American (%)	Download	0.15*	0.32**	-0.05	-0.20
		(0.08)	(0.15)	(0.09)	(0.12)
	Upload	0.17**	0.41***	0.16*	0.07
		(0.07)	(0.09)	(0.08)	(0.17)
American Indian and Alaska Native (%)	Download	-0.31	-0.95**	-0.86**	-1.25***
		(0.21)	(0.42)	(0.39)	(0.30)
	Upload	-0.14	-0.12	-0.30	-0.57*
		(0.16)	(0.23)	(0.27)	(0.32)
Asian (%)	Download	0.09	0.22	-0.22	-1.01***
		(0.15)	(0.19)	(0.27)	(0.25)
	Upload	0.05	0.05	0.05	-1.35***
		(0.16)	(0.19)	(0.25)	(0.37)
Hispanic or Latino (%)	Download	-0.24**	-0.16	-0.45***	-0.37**
		(0.10)	(0.17)	(0.10)	(0.16)
	Upload	0.11	0.25***	0.08	-0.39*
		(0.08)	(0.10)	(0.08)	(0.20)
Median Age (Log)	Download	-0.18*	-0.09	0.33***	-0.49***

		(0.10)	(0.15)	(0.10)	(0.13)
	Upload	-0.28***	-0.15*	-0.34***	-0.49***
		(0.07)	(0.09)	(0.09)	(0.18)
Mean Travel Time (Log)	Download	-0.17***	-0.17*	-0.06	-0.44***
		(0.06)	(0.09)	(0.06)	(0.07)
	Upload	-0.18***	-0.13**	-0.18***	-0.35***
		(0.04)	(0.06)	(0.05)	(0.10)
Mean Household Size (Log)	Download	-0.04	0.10	0.54***	0.64*
		(0.15)	(0.22)	(0.19)	(0.35)
	Upload	-0.21	-0.10	-0.12	0.93**
		(0.13)	(0.15)	(0.16)	(0.43)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.16: OLS Economic Variables

Dependent Variable	Independent Variable (Log(1+KBps))	Subsample 3G	4G Non-LTE	LTE	WiFi
Median Household Income (Log $)	Download	0.16**	0.23**	0.09	0.79***
		(0.07)	(0.11)	(0.09)	(0.10)
	Upload	0.14***	0.14**	0.10	0.72***
		(0.05)	(0.07)	(0.07)	(0.14)
Unemployed (%)	Download	-1.55*	-0.36	0.25	4.73***
		(0.90)	(1.46)	(1.02)	(1.11)
	Upload	-1.34**	-1.12	-1.56*	2.68*
		(0.66)	(0.99)	(0.86)	(1.49)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.17: OLS Technological Variables

Dependent Variable	Independent Variable (Log(1+KBps))	Subsample 3G	4G Non-LTE	LTE	WiFi
iOS	Download	0.51***		0.02***	-0.05***
		(0.02)		(0.01)	(0.01)
	Upload	0.14***		-0.07***	-0.05***
		(0.02)		(0.01)	(0.00)
Minimum Effect Radius (Log)	Download	-0.00	-0.11	-0.05	-0.08*
		(0.03)	(0.07)	(0.04)	(0.04)
	Upload	-0.06**	-0.12***	-0.12***	-0.08
		(0.03)	(0.04)	(0.04)	(0.06)
No telephone service (%)	Download	-0.80	-0.06	-1.36	-2.08**
		(0.55)	(1.05)	(0.86)	(0.82)

	Upload	-0.17	-0.39	-0.70	-2.28**
		(0.42)	(0.61)	(0.63)	(0.99)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.18: OLS Area Weighted Providers

		Subsample			
Dependent Variable	Independent Variable	3G	Non-LTE 4G	LTE	WiFi
Log(1 + Provider Count (Area Weighted))	Download	0.08	0.51***	-0.11	-0.27**
		(0.06)	(0.12)	(0.08)	(0.11)
	Upload	0.11**	0.12*	-0.20***	-0.30*
		(0.04)	(0.07)	(0.07)	(0.16)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.19: OLS Hour Fixed Effects

	Dependent Variable	Subsample			
	(Log(1+KBps))	3G	4G Non-LTE	LTE	WiFi
1:00 AM	Download	0.05**	0.13***	0.20***	0.05***
		(0.03)	(0.02)	(0.01)	(0.00)
	Upload	0.02	0.04**	0.09***	0.03***
		(0.03)	(0.02)	(0.01)	(0.00)
2:00 AM	Download	0.14***	0.24***	0.31***	0.08***
		(0.03)	(0.02)	(0.01)	(0.00)
	Upload	0.07**	0.09***	0.16***	0.05***
		(0.03)	(0.02)	(0.01)	(0.00)
3:00 AM	Download	0.13***	0.23***	0.39***	0.08***
		(0.03)	(0.03)	(0.02)	(0.01)
	Upload	0.05*	0.06**	0.19***	0.05***
		(0.03)	(0.03)	(0.01)	(0.00)
4:00 AM	Download	0.12***	0.29***	0.41***	0.08***
		(0.03)	(0.03)	(0.02)	(0.01)
	Upload	0.00	0.09***	0.20***	0.04***
		(0.03)	(0.02)	(0.01)	(0.01)
5:00 AM	Download	0.11***	0.21***	0.37***	0.06***
		(0.03)	(0.04)	(0.02)	(0.01)
	Upload	0.01	0.05**	0.17***	0.03***
		(0.03)	(0.02)	(0.01)	(0.01)
6:00 AM	Download	0.03	0.12***	0.22***	0.02***
		(0.02)	(0.03)	(0.01)	(0.00)

	Upload	-0.01	0.01	0.10***	0.02***
		(0.02)	(0.02)	(0.01)	(0.01)
7:00 AM	Download	-0.08***	0.01	0.00	-0.01***
		(0.02)	(0.02)	(0.01)	(0.00)
	Upload	-0.02	-0.03	0.02***	0.03***
		(0.02)	(0.02)	(0.01)	(0.00)
8:00 AM	Download	-0.15***	-0.08***	-0.12***	-0.03***
		(0.02)	(0.02)	(0.01)	(0.00)
	Upload	-0.07***	-0.08***	-0.05***	0.03***
		(0.02)	(0.02)	(0.01)	(0.00)
9:00 AM	Download	-0.17***	-0.13***	-0.19***	-0.03***
		(0.02)	(0.03)	(0.02)	(0.00)
	Upload	-0.06***	-0.11***	-0.09***	0.02***
		(0.02)	(0.02)	(0.01)	(0.00)
10:00 AM	Download	-0.19***	-0.17***	-0.25***	-0.04***
		(0.02)	(0.03)	(0.02)	(0.00)
	Upload	-0.08***	-0.12***	-0.12***	0.01**
		(0.02)	(0.02)	(0.01)	(0.00)
11:00 AM	Download	-0.22***	-0.20***	-0.31***	-0.04***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.09***	-0.12***	-0.13***	0.01
		(0.02)	(0.02)	(0.01)	(0.00)
12:00 PM	Download	-0.28***	-0.23***	-0.42***	-0.05***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.12***	-0.13***	-0.17***	-0.00
		(0.02)	(0.02)	(0.01)	(0.00)
1:00 PM	Download	-0.28***	-0.23***	-0.41***	-0.06***
		(0.02)	(0.03)	(0.02)	(0.00)
	Upload	-0.12***	-0.13***	-0.17***	0.00
		(0.02)	(0.02)	(0.01)	(0.00)
2:00 PM	Download	-0.27***	-0.24***	-0.43***	-0.05***
		(0.02)	(0.03)	(0.02)	(0.00)
	Upload	-0.12***	-0.14***	-0.18***	0.00
		(0.02)	(0.02)	(0.01)	(0.00)
3:00 PM	Download	-0.28***	-0.27***	-0.46***	-0.05***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.12***	-0.13***	-0.20***	-0.01***
		(0.02)	(0.02)	(0.01)	(0.00)
4:00 PM	Download	-0.28***	-0.26***	-0.48***	-0.04***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.10***	-0.14***	-0.20***	-0.02***
		(0.02)	(0.02)	(0.01)	(0.00)
5:00 PM	Download	-0.29***	-0.29***	-0.50***	-0.03***
		(0.02)	(0.03)	(0.02)	(0.00)

	Upload	-0.10***	-0.13***	-0.22***	-0.03***
		(0.02)	(0.02)	(0.01)	(0.00)
6:00 PM	Download	-0.28***	-0.28***	-0.49***	-0.04***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.12***	-0.13***	-0.23***	-0.03***
		(0.02)	(0.02)	(0.01)	(0.00)
7:00 PM	Download	-0.27***	-0.27***	-0.48***	-0.06***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.13***	-0.12***	-0.24***	-0.04***
		(0.02)	(0.02)	(0.01)	(0.00)
8:00 PM	Download	-0.27***	-0.27***	-0.49***	-0.09***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.12***	-0.11***	-0.26***	-0.06***
		(0.02)	(0.01)	(0.01)	(0.00)
9:00 PM	Download	-0.24***	-0.24***	-0.48***	-0.10***
		(0.02)	(0.02)	(0.02)	(0.00)
	Upload	-0.11***	-0.10***	-0.26***	-0.07***
		(0.02)	(0.02)	(0.01)	(0.00)
10:00 PM	Download	-0.16***	-0.19***	-0.38***	-0.09***
		(0.02)	(0.02)	(0.01)	(0.00)
	Upload	-0.07***	-0.07***	-0.20***	-0.06***
		(0.02)	(0.01)	(0.01)	(0.00)
11:00 PM	Download	-0.12***	-0.10***	-0.19***	-0.05***
		(0.02)	(0.02)	(0.01)	(0.00)
	Upload	-0.05***	-0.05***	-0.09***	-0.03***
		(0.02)	(0.01)	(0.00)	(0.00)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.20: OLS Carrier Fixed Effects

Dependent Variable	Independent Variable (Log(1+KBps))	Subsample 3G	4G Non-LTE	LTE	WiFi
AT&T	Download	0.67***	0.17***	0.54***	0.21***
		(0.02)	(0.04)	(0.03)	(0.01)
	Upload	-0.08***	-0.09***	0.26***	0.15***
		(0.03)	(0.02)	(0.04)	(0.01)
AT&T Affiliate	Download	0.51***	-0.06	-0.52***	0.07***
		(0.03)	(0.04)	(0.03)	(0.01)
	Upload	-0.12***	-0.19***	0.09**	0.03***
		(0.03)	(0.02)	(0.04)	(0.01)
Sprint	Download	-0.38***		-0.06**	0.31***
		(0.03)		(0.03)	(0.01)
	Upload	-0.12***		-0.22***	0.21***
		(0.02)		(0.04)	(0.01)
Sprint Affiliate	Download	-0.50***		-0.49***	-0.11***
		(0.03)		(0.03)	(0.01)
	Upload	-0.25***		-0.42***	-0.11***
		(0.03)		(0.04)	(0.01)
T-Mobile	Download	0.45***	0.36***	0.42***	0.27***
		(0.03)	(0.03)	(0.05)	(0.01)
	Upload	-0.28***	0.20***	0.60***	0.20***
		(0.02)	(0.03)	(0.04)	(0.01)
T-Mobile Affiliate	Download	0.33***	0.01	-0.30***	-0.03***
		(0.05)	(0.05)	(0.06)	(0.01)
	Upload	-0.33***	0.04	0.31***	-0.06***
		(0.05)	(0.03)	(0.04)	(0.01)
Verizon	Download	-0.48***		0.56***	0.27***
		(0.02)		(0.03)	(0.01)
	Upload	-0.18***		0.17***	0.22***
		(0.02)		(0.04)	(0.01)
US Cellular	Download	-0.35***		0.02	0.15***
		(0.05)		(0.04)	(0.02)
	Upload	-0.23***		0.03	0.15***
		(0.04)		(0.05)	(0.03)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.21: OLS State Fixed Effects

Dependent Variable	Independent Variable (Log(1+KBps))	Subsample 3G	4G Non-LTE	LTE	WiFi
AK	Download	-0.38**	-0.25	-0.27**	-0.42***
		(0.18)	(0.18)	(0.11)	(0.10)
	Upload	-0.07	0.17*	0.21**	-0.35**
		(0.11)	(0.09)	(0.10)	(0.14)
AZ	Download	0.11**	0.21***	-0.14*	0.19**
		(0.05)	(0.08)	(0.08)	(0.09)
	Upload	0.17***	0.13**	-0.21***	0.22**
		(0.04)	(0.06)	(0.06)	(0.10)
AR	Download	-0.00	-0.01	-0.13**	-0.06
		(0.07)	(0.09)	(0.06)	(0.06)
	Upload	-0.07	-0.05	-0.08	0.03
		(0.06)	(0.08)	(0.06)	(0.08)
CA	Download	0.07	-0.04	-0.15**	-0.13*
		(0.06)	(0.09)	(0.07)	(0.08)
	Upload	-0.11**	-0.24***	-0.18**	-0.16
		(0.05)	(0.07)	(0.08)	(0.11)
CO	Download	0.03	0.23***	-0.28***	-0.00
		(0.06)	(0.08)	(0.05)	(0.07)
	Upload	-0.01	0.13**	-0.52***	0.02
		(0.05)	(0.06)	(0.06)	(0.10)
CT	Download	-0.00	-0.07	-0.15**	-0.07
		(0.06)	(0.10)	(0.08)	(0.08)
	Upload	-0.07*	-0.20**	-0.25***	-0.01
		(0.04)	(0.08)	(0.06)	(0.10)
DE	Download	-0.12	-0.13	-0.25***	0.25***
		(0.08)	(0.08)	(0.06)	(0.08)
	Upload	0.01	-0.17**	-0.38***	0.65***
		(0.04)	(0.07)	(0.08)	(0.07)
DC	Download	-0.34***	-0.68***	-0.20***	-0.53***
		(0.05)	(0.08)	(0.06)	(0.10)
	Upload	-0.15***	-0.47***	-0.43***	-0.27**
		(0.04)	(0.06)	(0.06)	(0.13)
FL	Download	0.20***	0.27***	0.04	0.25***
		(0.05)	(0.07)	(0.04)	(0.06)
	Upload	0.01	0.03	-0.11**	0.51***
		(0.04)	(0.06)	(0.05)	(0.10)
GA	Download	0.10**	0.18**	0.08*	0.01
		(0.04)	(0.07)	(0.04)	(0.04)
	Upload	0.04	0.04	0.02	0.14*
		(0.04)	(0.06)	(0.06)	(0.08)
HI	Download	-0.10	-0.03	-0.38**	0.10
		(0.10)	(0.18)	(0.19)	(0.13)
	Upload	-0.14	-0.03	-0.01	0.03

		(0.09)	(0.12)	(0.14)	(0.18)
ID	Download	-0.11	-0.39***	-0.33***	-0.29***
		(0.09)	(0.14)	(0.12)	(0.07)
	Upload	-0.07	-0.19**	-0.19**	-0.34***
		(0.05)	(0.09)	(0.09)	(0.11)
IL	Download	0.16***	0.29***	0.04	-0.09
		(0.05)	(0.07)	(0.06)	(0.07)
	Upload	0.09**	0.25***	0.08	0.07
		(0.04)	(0.06)	(0.06)	(0.10)
IN	Download	-0.02	-0.06	0.05	-0.06
		(0.05)	(0.08)	(0.05)	(0.06)
	Upload	-0.08*	-0.02	-0.04	0.25**
		(0.04)	(0.06)	(0.05)	(0.10)
IA	Download	-0.04	0.20	0.09*	-0.12
		(0.12)	(0.12)	(0.05)	(0.08)
	Upload	0.01	0.30***	0.19***	0.23**
		(0.07)	(0.09)	(0.05)	(0.10)
KS	Download	0.28***	0.35***	0.18***	0.04
		(0.07)	(0.08)	(0.06)	(0.12)
	Upload	0.13**	0.25***	0.03	0.44**
		(0.06)	(0.08)	(0.07)	(0.20)
KY	Download	-0.02	-0.12	-0.05	-0.01
		(0.05)	(0.11)	(0.05)	(0.06)
	Upload	-0.12**	-0.07	-0.08	0.19**
		(0.05)	(0.07)	(0.06)	(0.09)
LA	Download	0.02	-0.04	-0.22***	0.10**
		(0.05)	(0.11)	(0.06)	(0.05)
	Upload	0.06	0.08	-0.18***	0.17**
		(0.04)	(0.11)	(0.06)	(0.08)
ME	Download	0.04	0.03	-0.43***	-0.14*
		(0.06)	(0.18)	(0.10)	(0.08)
	Upload	-0.06	-0.25**	-0.51***	-0.15
		(0.06)	(0.11)	(0.12)	(0.12)
MD	Download	-0.19***	-0.39***	-0.21***	0.06
		(0.07)	(0.10)	(0.05)	(0.06)
	Upload	-0.06	-0.21***	-0.32***	0.42***
		(0.05)	(0.07)	(0.05)	(0.10)
MA	Download	0.00	-0.02	-0.12**	0.06
		(0.05)	(0.07)	(0.05)	(0.08)
	Upload	-0.05	-0.18***	-0.20***	0.25**
		(0.05)	(0.06)	(0.05)	(0.12)
MI	Download	-0.17***	0.09	0.19***	-0.08*
		(0.05)	(0.08)	(0.04)	(0.05)
	Upload	-0.09**	0.02	0.04	0.10
		(0.04)	(0.06)	(0.05)	(0.08)
MN	Download	0.04	0.21***	0.23***	-0.07
		(0.06)	(0.08)	(0.05)	(0.06)
	Upload	-0.04	0.04	0.07	0.02

		(0.04)	(0.06)	(0.05)	(0.09)
MS	Download	0.02	0.04	-0.17***	0.01
		(0.05)	(0.09)	(0.05)	(0.06)
	Upload	0.01	-0.04	-0.09	0.08
		(0.05)	(0.07)	(0.05)	(0.09)
MO	Download	0.03	0.11	-0.00	0.04
		(0.04)	(0.07)	(0.05)	(0.07)
	Upload	-0.08*	0.05	-0.15***	0.14
		(0.05)	(0.07)	(0.06)	(0.17)
MT	Download	-0.11	-0.31**	-0.34***	-0.01
		(0.12)	(0.15)	(0.10)	(0.09)
	Upload	0.03	-0.14	-0.26***	0.12
		(0.09)	(0.10)	(0.09)	(0.11)
NE	Download	0.18*	0.52***	-0.01	-0.11*
		(0.10)	(0.14)	(0.07)	(0.06)
	Upload	-0.01	0.06	0.08	-0.01
		(0.06)	(0.08)	(0.10)	(0.11)
NV	Download	0.12*	-0.02	-0.37***	0.06
		(0.06)	(0.10)	(0.08)	(0.08)
	Upload	0.20***	-0.02	-0.06	0.15
		(0.08)	(0.08)	(0.07)	(0.12)
NH	Download	0.14***	0.15*	-0.27***	0.20**
		(0.04)	(0.08)	(0.10)	(0.08)
	Upload	0.05	-0.11	-0.39***	0.24**
		(0.04)	(0.07)	(0.12)	(0.10)
NJ	Download	0.00	-0.26**	-0.13**	0.05
		(0.05)	(0.10)	(0.06)	(0.06)
	Upload	0.05	-0.22***	-0.11**	0.56***
		(0.04)	(0.07)	(0.06)	(0.10)
NM	Download	0.21**	0.12	-0.17	0.20*
		(0.09)	(0.18)	(0.11)	(0.10)
	Upload	0.14**	0.15	-0.08	0.17
		(0.06)	(0.11)	(0.09)	(0.16)
NY	Download	-0.06	-0.25***	-0.10*	-0.13**
		(0.04)	(0.07)	(0.05)	(0.06)
	Upload	-0.07*	-0.28***	-0.20***	0.30***
		(0.04)	(0.06)	(0.06)	(0.11)
NC	Download	0.22***	0.10	-0.19***	0.18***
		(0.04)	(0.08)	(0.05)	(0.04)
	Upload	0.06*	-0.18***	-0.18***	0.40***
		(0.03)	(0.06)	(0.05)	(0.07)
ND	Download	-0.10	-0.37**	0.18***	0.43***
		(0.12)	(0.18)	(0.06)	(0.07)
	Upload	0.04	-0.12	0.23***	0.69***
		(0.09)	(0.18)	(0.06)	(0.14)
OH	Download	-0.00	0.06	0.14**	-0.28***
		(0.05)	(0.07)	(0.06)	(0.05)
	Upload	0.05	0.08	-0.09*	-0.27***

		(0.04)	(0.06)	(0.05)	(0.08)
OK	Download	0.20***	-0.01	-0.08	-0.01
		(0.06)	(0.20)	(0.08)	(0.07)
	Upload	0.08	0.11	0.06	-0.04
		(0.05)	(0.12)	(0.07)	(0.08)
OR	Download	0.04	0.10	0.11*	0.05
		(0.06)	(0.10)	(0.06)	(0.07)
	Upload	0.01	0.15*	-0.14**	0.21**
		(0.06)	(0.08)	(0.06)	(0.11)
PA	Download	0.03	0.03	-0.04	0.02
		(0.05)	(0.08)	(0.07)	(0.05)
	Upload	0.03	-0.02	-0.11	0.30***
		(0.04)	(0.07)	(0.07)	(0.11)
RI	Download	0.04	0.13	0.08	0.11
		(0.09)	(0.10)	(0.06)	(0.07)
	Upload	-0.11*	-0.22**	-0.01	0.76***
		(0.06)	(0.09)	(0.09)	(0.15)
SC	Download	0.09	0.24***	-0.20***	-0.09
		(0.06)	(0.08)	(0.06)	(0.06)
	Upload	0.09**	-0.02	-0.04	-0.08
		(0.04)	(0.07)	(0.05)	(0.09)
SD	Download	-0.08	-0.21	0.15**	0.16**
		(0.09)	(0.19)	(0.06)	(0.06)
	Upload	-0.03	-0.09	0.07	0.40***
		(0.06)	(0.14)	(0.07)	(0.10)
TN	Download	-0.02	0.04	-0.15***	0.11
		(0.04)	(0.10)	(0.05)	(0.07)
	Upload	-0.02	0.06	-0.03	0.41***
		(0.04)	(0.06)	(0.07)	(0.12)
TX	Download	0.11**	-0.03	-0.11**	0.04
		(0.04)	(0.08)	(0.05)	(0.06)
	Upload	-0.02	0.10	-0.19***	0.16
		(0.04)	(0.06)	(0.05)	(0.10)
UT	Download	-0.05	-0.36***	-0.43***	-0.23***
		(0.07)	(0.10)	(0.07)	(0.07)
	Upload	0.05	-0.11	-0.24***	-0.07
		(0.05)	(0.07)	(0.07)	(0.10)
VT	Download	-0.08	-0.64***	-0.49***	-0.03
		(0.08)	(0.14)	(0.07)	(0.09)
	Upload	-0.09*	-0.32***	-0.69***	0.15
		(0.05)	(0.10)	(0.08)	(0.12)
VA	Download	-0.02	-0.29***	-0.28***	-0.10**
		(0.06)	(0.09)	(0.05)	(0.05)
	Upload	-0.02	-0.23***	-0.36***	0.25***
		(0.04)	(0.06)	(0.05)	(0.09)
WA	Download	0.01	0.30**	0.13*	0.06
		(0.06)	(0.12)	(0.07)	(0.07)
	Upload	0.02	0.20**	-0.04	0.12

		(0.06)	(0.10)	(0.08)	(0.11)
WV	Download	0.00	-0.16	-0.24***	0.18**
		(0.06)	(0.15)	(0.06)	(0.07)
	Upload	-0.07	-0.09	-0.07	0.30***
		(0.05)	(0.10)	(0.06)	(0.09)
WI	Download	-0.11**	-0.08	0.09*	-0.20**
		(0.05)	(0.08)	(0.05)	(0.08)
	Upload	-0.16***	-0.01	-0.05	-0.20*
		(0.04)	(0.08)	(0.07)	(0.11)
WY	Download	-0.53***	0.31*	-0.56***	0.03
		(0.16)	(0.17)	(0.16)	(0.09)
	Upload	0.03	0.44***	-0.41***	0.14
		(0.07)	(0.11)	(0.11)	(0.13)
Constant	Download	6.18***	5.67***	6.69***	3.20***
		(0.60)	(0.98)	(0.71)	(0.82)
	Upload	6.47***	6.19***	8.95***	1.83
		(0.43)	(0.64)	(0.60)	(1.22)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1